A social driving style of highly automated vehicles from cyclists' perspective

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A social driving style of highly automated vehicles from cyclists' perspective

by

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Cover image: https://www.bicycling.com/culture/a42111006/are-cyclists-safe-around-self-driving-cars/

Preface

The current project, titled “A social driving style of highly automated vehicles from cyclists’ perspective", has been written to fulfil the graduation requirements of the Transport, Infrastructure and Logistics program at the Delft University of Technology in the Netherlands. This project signifies the completion of my academic journey. Reflecting on this journey, I realise how much I have learned, not only in terms of knowledge but also about myself. The path was filled with challenges that initially seemed overwhelming, but through constant effort and persistence, I managed to overcome them.

Before I invite you to read my thesis, I would like to express my gratitude to the people who have supported me throughout this research process. First, I would like to thank my academic supervisors, Dr. Haneen Farah, who served as the chair of my thesis committee and helped me select my thesis topic, Dr. Eleonora Papadimitriou and Dr. Jan Anne Annema. Their expertise and experience in the field of Transportation Engineering were immensely helpful and their valuable suggestions and feedback made this thesis more comprehensive and insightful.

Further, I would like to thank those involved in this project. Specifically, the experts who participated in the construction of the conceptual framework. Their feedback was invaluable and helped create a functional and scientifically solid framework, which in turn facilitated the analysis process. I also extend my gratitude to all the participants of my survey. Their contributions provided critical insights into my thesis topic and were essential in completing the thesis.

Last but not least, I would like to thank my friends, who always stood by my side and kept me going during my studies and my thesis work. A special thanks goes to my family. Without their wholehearted support, hope and inspiration, I would not have been able to reach this point.

Dear reader, I hope you enjoy reading.

Alexandros Dimitroulis

Delft, August 2024

Executive summary

Background and problem description

The introduction of Highly Automated Vehicles (HAVs) into real traffic conditions constitutes a great challenge for urban mobility. As with every new technology, HAVs might be dealt with too favourably by some experts by pointing out mostly their strong points such as traffic flow enhancement and improvement of road safety and accessibility, while others remain sceptical, focusing on possible drawbacks that are related to the physical integrity of the other traffic participants (i.e., other drivers, cyclists and pedestrians).

In addition, the fact that HAVs do not require an active driver and by extension, the possibility of communication between the user of an HAV and another traffic participant may be reduced, it is likely to create a form of doubt, if not distrust, to the other road users exactly due to this void gap. Due to the increased automation levels of HAVs, the need for manual intervention by the HAV owner is expected to be minimal. This necessitates the adoption of a socially compliant driving style by the HAV. Socially compliant driving is a term that has been defined as the predictable behaviour of HAVs in interactions with humans and autonomous agents. In the context of HAVs, social compliance is influenced by factors like the driving style, the way the HAV communicates its intentions and also the way an HAV adapts its behaviour in mixed traffic conditions.

In urban settings, where many different road users coexist, the probability of negotiating at unsignalised intersections is higher than driving on a highway. The focus of this research lies in the examination of the interaction of cyclists with HAVs. Cyclists are part of what is called Vulnerable Road Users (VRUs), as they travel with relatively minimal protection in comparison with drivers of conventional vehicles, meaning that they are at higher risk of being severely injured. They share, as pedestrians, eye-gazing behaviour as they focus more on the road ahead and conduct fewer shoulder checks.

Hence, achieving a social driving style for HAVs is a challenge, making it important to grasp a comprehensive understanding of relevant factors involved in the cyclist-HAV interaction.

Research aim and research question

From the literature review, a knowledge gap was identified and this is related to the lack of investigation into cyclists' perspective on the so-called social driving of HAVs. Consequently, the main research question was formulated to investigate the factors that cyclists deem crucial for the social driving behaviour of HAVs.

Main Research Question:	*What factors do cyclists consider important for the social driving behaviour of HAVs?*

Methodology

To address the main research question, a hybrid approach combining qualitative and quantitative methodologies was utilised. Through the literature review, valuable data were collected, which facilitated the construction of a conceptual framework describing the cyclist-HAV interaction. Subsequently, through expert interviews with professors of Delft University of Technology, it was possible to make the conceptual framework more valid and have stronger theoretical foundations. Hence, this conceptual model essentially served as a basis for the survey.

The survey consisted of four sections, namely:

a) ***Demographics***, where participants provided information about their age, gender, their frequency of cycling, whether they had any previous experience with automated vehicles (AVs) and their level of education;
b) ***People's perspectives on Socially Compliant HAV driving***, where people reported their familiarity with the concept of socially compliant driving of HAVs and subsequently answered an open-ended question regarding the specific behaviours or actions by HAVs that contribute to socially compliant driving;
c) ***Statements on cyclists' perceptions and attitudes towards HAVs***, where eight statements were assessed by respondents using a Likert scale from 1 (Disagree) to 5 (Agree);
d) ***Scenario-based Questions***, where seven scenarios were examined at unsignalised intersections and shared roadways. Again, these scenarios were assessed using a Likert scale from 1 to 5 assessing people's levels of Trust, Perceived Safety and Perceived Social Behaviour. In each Scenario, there was a multiple choice question asking respondents' potential reaction to each scenario, with the potential responses being "*Continue cycling at a constant speed*", "*Brake*", "*Accelerate*" or "*Other*".

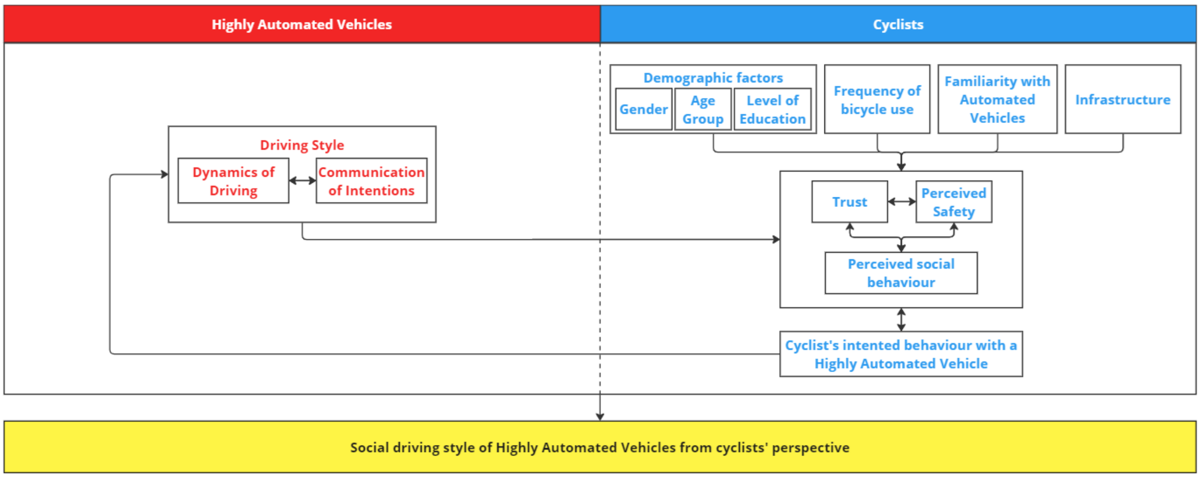
In total, the survey gathered 76 participants. After collecting the raw data from the survey, a descriptive analysis was conducted to gain insights into the conditions under which cyclists perceive an HAV to drive in a social manner.

Subsequently, several statistical tests were performed, such as Bivariate Correlation Analysis, Repeated Measures One-Way ANOVA and Multinomial Logistic Regression, to explore the factors influencing cyclists' perceptions and expectations of HAVs regarding Trust, Perceived Safety and Perceived Social Behaviour. The analysis also examined whether Trust, Perceived Safety and Perceived Social Behaviour affect cyclists' intended behaviour and investigated if any additional factors might influence this behaviour.

Results

The conceptual framework depicted essential elements involved in the interaction between HAVs and cyclists. Despite HAVs being machines, their use of sensors and electronics can partially bridge the negotiation gap with cyclists, allowing for consideration of a feedback loop between them. Specifically, concerning HAVs, driving style was placed as the primary determinant within this segment, including dynamics of driving (e.g., smooth/sharp acceleration) and the communication of HAV's intentions.

Subsequently, it was suggested that driving style had a significant impact on cyclists' Trust, Perceived Safety and Perceived Social Behaviour of HAVs. These three variables were proposed to be interconnected and influenced by factors such as demographics, cycling frequency, familiarity with AVs and cycling infrastructure (e.g., shared roadways or separated bicycle lanes). Consequently, Trust, Perceived Safety and Perceived Social Behaviour collectively influenced how cyclists reacted to interactions with HAVs. There was also speculation that cyclists' intended behaviour could reciprocally affect levels of Trust, Perceived Safety and Perceived Social Behaviour. Finally, the cyclist's reaction was assumed to affect the driving style of HAV.



The descriptive analysis of the survey revealed that the sample was predominantly comprised of younger participants who cycled frequently, with males being overrepresented. It is noteworthy that nearly 70% of respondents reported having some prior experience with automated vehicles in general. Regarding participants' educational level, a significant majority held either a Bachelor's or Master's degree. It is worth mentioning that there was a notable underrepresentation of individuals who received less advanced levels of education. When asked to express their views on the constituents of socially compliant driving from HAVs' side, respondents focused on aspects such as adherence to speed limits by HAVs, predictable driving behaviour, prioritisation of cyclists by HAVs and their rule compliance.

Additionally, participants evaluated eight statements, revealing that they considered the predictability of HAVs an important feature of their interaction with these vehicles. Additionally, the implementation of eHMIs was overwhelmingly supported. Participants thought that HAVs were more likely to comply with traffic rules than human drivers. Nevertheless, scepticism was expressed regarding HAVs' ability to effectively communicate their intentions, whether HAVs would prioritise cyclists and whether cyclists could predict HAV behaviour in various scenarios. Participants' opinions on these statements were supported by their responses to scenarios, where high ratings for Trust, Perceived Safety and Perceived Social behaviour were given in instances where HAVs moved predictably (i.e., driving at constant speed or decelerating), prioritised cyclists and utilised eHMI.

Regarding the factors influencing cyclists' perceptions and expectations, a bivariate analysis was employed to find strong correlations for each dependent variable (i.e., Trust, Perceived Safety and Perceived Social Behaviour) among demographics and HAV-related statements. It was found that cyclists' comfortability in sharing the road with HAVs, the use of eHMIs and rule compliance of HAVs' showed a strong correlation with the dependent variables.

Through the implementation of Repeated Measures One-Way ANOVA statistical test, it was validated that the HAVs equipped with eHMI significantly influence Trust, Perceived Safety and Perceived Social Behaviour. Moreover, it was found that people's comfortability in sharing the roads with HAVs and the frequency of cycling also influence Trust, Perceived Safety and Perceived Social Behaviour. In addition, it is noteworthy that rule compliance significantly impacts Perceived Safety and Perceived Social Behaviour more than the various scenario variations do.

Finally, to determine if cyclists' intended reactions were influenced by Trust, Perceived Safety and Perceived Social Behaviour, a Multinomial Logistic Regression test was used. The results showed that these three factors, along with the individual's age group, familiarity with the concept of socially compliant driving and experience with HAVs, significantly affected cyclists' intended reactions.

Conclusions

Analysis indicated that cyclists prefer to avoid engaging in unpleasant situations, especially where there is a lack of clarity or predictability regarding the intentions of HAVs. This was evident from the results of scenarios at unsignalised intersections. Consequently, a widely supported measure to mitigate these issues, as evidenced by the survey respondents, is the use of eHMIs by HAVs. The implementation of eHMIs appears to positively influence cyclists' Trust, Perceived Safety and Perceived Social Behaviour. Furthermore, people’s comfortability in sharing roads with HAVs and the frequency with which they cycle also seemed to positively affect Trust, Perceived Safety and Perceived Social Behaviour. Additionally, the rule compliance of HAVs significantly enhances Perceived Safety and Perceived Social Behaviour, more so than the various scenarios analysed. Contrary to the findings of other studies, for this research demographic factors did not seem to exert a significant influence on people’s perceptions concerning their interaction with HAVs.

The study mainly consulted technical experts, which could potentially limit the perspectives on how HAVs behave socially. Future research could involve a wider range of experts to develop more detailed frameworks. Also, since most participants were from the Netherlands, which has a strong cycling culture, findings may not apply universally. To improve this, future studies should include diverse cultural contexts to better understand interactions between cyclists and HAVs in different traffic settings.

Besides, future research could concentrate on specific areas to improve understanding of cyclist-HAV interactions. These could include conducting long-term studies to track evolving perceptions of HAV technology among cyclists, exploring interdisciplinary approaches to inform user-friendly HAV systems and investigating the potential influence of environmental factors on cyclist-HAV interactions.

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Abbreviations

ANOVA: Analysis of Variance

AV: Automated Vehicle

eHMI: External Human-Machine Interface

FAV: Fully Automated Vehicle

HAV: Highly Automated Vehicle

HDV: Human-Driven Vehicle

HMI: Human-Machine Interface

I2V: Infrastructure to Vehicle

ITS: Intelligent Transportation System

MNLR: Multinomial Logistic Regression

SVO: Social Value Orientation

UTAUT: Unified Theory of Acceptance and Use of Technology

VR: Virtual Reality

VRU: Vulnerable Road User

1. Introduction

1.1. Background

As Highly Automated Vehicles (HAVs) are expected to become integral to global road networks, the automotive industry anticipates a significant shift. Autonomous driving systems are predicted to be prevalent in most new vehicles by 2030 (Berge et al., 2024). This technology aims to transform transportation by improving traffic flow and road safety while reducing accidents caused by human error (Papadimitriou et al., 2020). Over 90% of road accidents result from human factors like speeding, distraction and inexperience (Papadimitriou et al., 2020). In general, HAVs are expected to outperform human drivers by avoiding risky behaviours (Liu, 2023).

Moreover, the adoption of HAVs is anticipated to enhance real-time route planning, energy efficiency and capacity management (MIT Technology Insights, 2020). They also promise improved accessibility for older adults and people with disabilities and more sustainable mobility through shared services of automated vehicles (AVs) (Bonnefon et al., 2020; Cordts et al., 2021; Mohammadzadeh, 2021). Autonomous driving is seen as crucial to the "smart city" concept, promoting sustainability, safety and efficient mobility (IEEE, n.d.).

Despite the benefits, growing interest in autonomous driving brings public concerns. Issues such as fairness in transportation (e.g., the cost of HAVs compared to conventional vehicles) and road safety (e.g., the risk of hacking causing accidents) are prominent (Santoni de Sio, 2021; Othman, 2022; Bagloee et al., 2016). Additionally, there are worries about overlapping responsibilities (Hansson, 2020). Effective interaction with other road users, such as cyclists, through socially compliant behaviour is crucial for integrating HAVs into current transportation systems (Vinkhuyzen & Cefkin, 2016).

Public perceptions of HAVs are mixed, encompassing both positive and negative views (Ngwu et al., 2022). As HAV technology evolves, traffic communication becomes increasingly vital, especially for vulnerable road users (VRUs) like cyclists and pedestrians. Their safety is paramount, given the lack of physical protection compared to vehicle occupants (Ngwu et al., 2022). Imanishimwe and Kumar (2023) stress the need to understand HAVs' impact on road safety and VRU well-being, given concerns about AV-related traffic accidents and fatalities. Cyclist injuries have risen in areas with poor integration between vehicles and bicycles, highlighting VRU safety issues (Li et al., 2023). Boufous et al. (2012) note that bicycle incidents involving motor vehicles are common, with 34% resulting in serious injuries for cyclists.

Cycling is a viable alternative to driving, offering reduced travel times while meeting daily needs. It is especially popular in the Netherlands, where it is a preferred mode of transport (Berge et al., 2022). However, cyclists face challenges, particularly at intersections where they have the right of way but are uncertain about approaching vehicles' actions (Vlakveld et al., 2020). Mohammadi et al. (2023) report an increase in cyclist fatalities, particularly at unsignalised intersections where cyclists and motor vehicles intersect. Although drivers are generally expected to yield to cyclists, many fail to do so in practice (Mohammadi et al., 2023). Conversely, cyclists who used to have priority may engage in risky behaviours, such as ignoring traffic signals (Berge et al., 2022). Therefore, integrating HAVs effectively is crucial for safe interactions between cyclists and AVs (Bjørnskau et al., 2023).

1.2. Research problem

Social driving is a key factor for the success of this technology enterprise. Schwarting et al. (2019) define socially compliant driving as predictable behaviour in interactions with humans and autonomous agents, while Vinkhuyzen and Cefkin (2016) describe it as the behaviour of AVs in specific traffic interactions. Social compliance is influenced by factors such as trust or the driving style of HAVs. Yet, limited attention has been given to the interactions among these factors and their impact on the gradual implementation of HAVs alongside cyclists. The fact that the cyclists are VRUs, travelling with minimal protection, means that they face higher risk regarding their physical integrity.

Hence, it is essential to investigate how cyclists perceive and respond to HAVs at Levels 4 and 5 of automation, particularly in terms of social driving and their expectations. To provide context, it is important to briefly describe the features of these levels. According to Liu et al. (2022), Level 4 AVs can control all driving tasks autonomously but only under specific conditions, such as within designated areas (i.e., geofencing). In contrast, Level 5 vehicles can operate independently without any human intervention in any situation.

Vlakveld et al. (2020) observed that while earlier studies predominantly examined pedestrian behaviour at unsignalised crossings, there is still a lack of experimental research from the cyclist’s viewpoint. This gap prevents a full understanding of the interactions and specifically the factors that are involved between cyclists and HAVs. Therefore, the identified knowledge gap in the literature is the lack of investigation into cyclists' perceptions of the social compliance of HAV components. Understanding the dynamics between trust, perceived safety and perceived social behaviour of HAVs from the cyclist's viewpoint will provide valuable insights into enhancing the social compliance of HAVs, contributing to safer interactions between HAVs and cyclists.

Chapter 2.4. in the literature review chapter provides a more comprehensive exploration of the previously mentioned knowledge gap.

1.3. Research gap, objective and questions

As stated earlier, attaining social compliance concerning HAVs is a difficult challenge that requires a thorough comprehension of all relevant factors. As noted in the previous subsection, this literature review essentially explores two main features, namely cyclists as VRUs and the aspects of social compliance regarding HAVs. Consequently, this study aims to answer the following research question to offer a better understanding of what socially compliant HAV driving behaviour through cyclists' viewpoint entails.

- ***Research Question**: What factors do cyclists consider important for the social driving behaviour of HAVs?*

This research topic is supplemented by supporting sub-questions that will shed light on important aspects, thus allowing for the development of a proper research structure and ultimately a more comprehensive picture. As a result, four sub-questions emerged, which are as follows:

- ***Sub-question 1**: What are the conceptual determinants of socially compliant driving behaviour?*
- ***Sub-question 2**: Under which conditions do cyclists perceive a HAV to drive in a social manner?*
- ***Sub-question 3**: Which factors influence cyclists' perceptions and expectations of HAVs regarding Trust, Perceived Safety and Perceived Social Behaviour?*
- ***Sub-question 4**: Do Trust, Perceived Safety and Perceived Social Behaviour affect cyclists' intended behaviour? If so, what other factors might also influence this intended behaviour?*

The first sub-question follows an expert-based approach, while the subsequent sub-questions target a specific user-based approach, namely that of cyclists. The second sub-question deals with the scenario characteristics and quantifies the gauging levels of Trust, Perceived Safety and Perceived Social Behaviour. The third sub-question investigates the factors that influence cyclists' perceptions and expectations when it comes to their interaction with HAVs. The fourth sub-question explores the factors under which cyclists' reactions can be modelled.

Subsequently, when these questions are adequately answered, a clearer view of the expectations and perceptions of cyclists about these concepts will emerge and by extension, both manufacturers and policymakers will have a more comprehensive understanding of how to design and implement socially compliant driving behaviour for HAVs.

1.4. Report structure

The structure of this thesis consists of six chapters focusing on various dimensions. First, the introduction in Chapter 1 provides an overview of the topic including HAVs and VRUs and outlines the main challenges that are associated with these domains. In Chapter 2, the research methodology covers the criteria for selecting scientific papers. This chapter is divided into two sub-sections: one aimed at presenting the perspective of cyclists regarding their interaction with HAVs, covering aspects such as their perceptions, trust, perceived safety, acceptance and expectations. The other sub-section focuses on the HAV aspect, presenting elements such as driving style, the communication of intentions and their behavioural adaptation. Following this, Chapter 3 describes the study's methodological approach, beginning with the research and survey design. It then explains the participant recruitment process, as well as the data collection and analysis techniques. Furthermore, it discusses the reasoning behind scenario selection and design. Moving forward, Chapter 4 delves into the presentation of the conceptual framework and the analysis of the survey data, providing an interpretation of the findings. In Chapter 5, a discussion of the results of the research takes place and addresses aspects as well as any limitations encountered, while it also offers recommendations for future research and suggests areas for improvement. Last but not least, in Chapter 6 the research findings are synthesised, highlighting key conclusions drawn from the study.

The chart in Figure 1 provides an overview of the thesis structure.

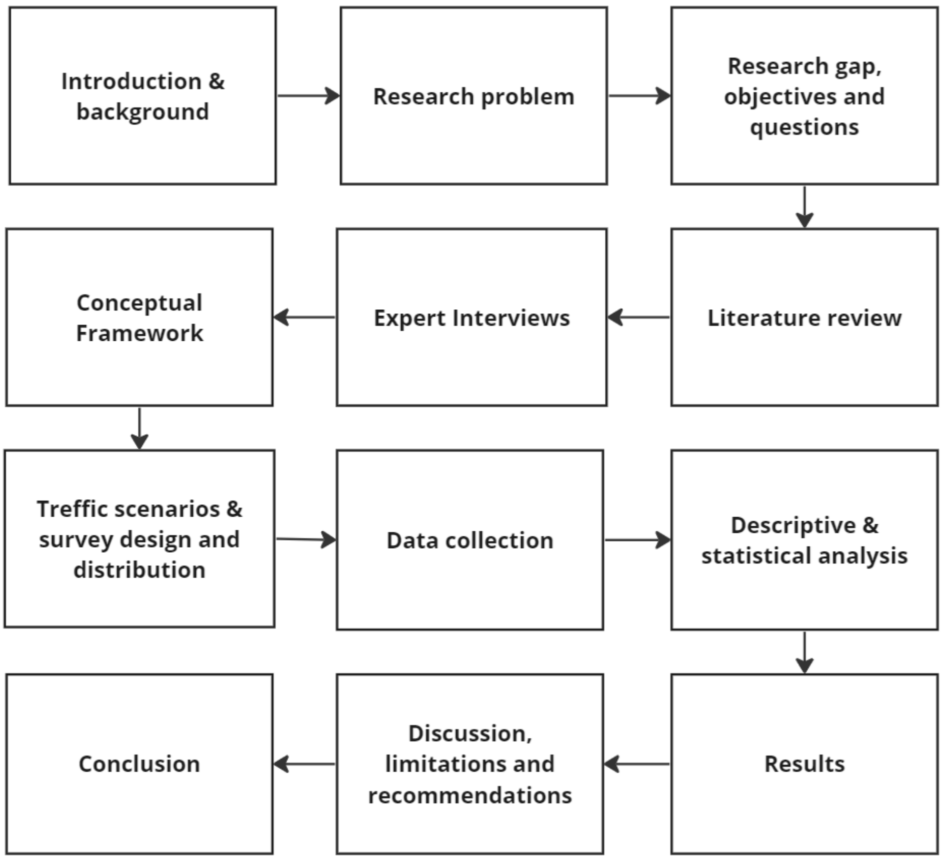


***Figure 1**: Structure of the thesis*

2. Literature review

The aim of this literature review is to explore two fundamental dimensions: the perspective of cyclists, a particularly vulnerable group of road users, in their interactions with HAVs and the crucial concept of social compliance in the field of HAV technology. This review delves into cyclists' perceptions toward HAVs, offering insights into their expectations, perceptions and concerns. Simultaneously, the study explores various aspects with respect to social compliance in HAVs, such as their driving style, the way they communicate their intentions and their behavioural adaptation.

2.1. Research methodology for the literature review

The main objective of this literature review is to explore various perspectives and effectively address the knowledge gap introduced in the previous chapter. To achieve this, a critical review approach is employed, evaluating research findings related to the central themes of this research. These themes consist of two key pillars: a) the role of cyclists as VRUs and b) the concept of social compliance in HAV driving. Each of these pillars is further subdivided into specific subtopics, enhancing the depth and breadth of the examination. Figure 2 below provides a clearer overview of the structure and organisation of this review.

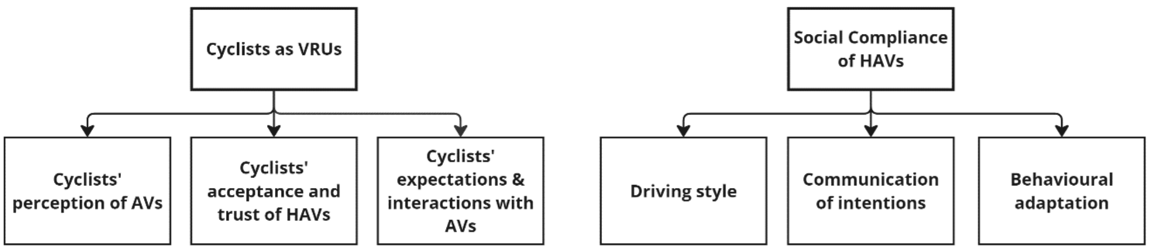


***Figure 2**: Main pillars of the literature review*

Regarding the search strategy, it is first important to mention the databases from which the scientific papers were extracted. More accurately, through three databases the majority of the research was done, namely: a) ScienceDirect, b) Scopus and c) Google Scholar. The criteria set for this research was to include certain keywords for each of these two pillars, with the objective of addressing the main components of this literature review. Moreover, the subject areas were limited to the fields of “engineering”, “decision sciences” and “social sciences”. The selected strategy is justified by the fact that, as a new technology, HAVs have several dimensions. Since HAV technology is a rather new one, engineering is primarily concerned with the development and technical elements of HAVs. Meanwhile, the decision sciences are essential in developing the deterministic processes that control the actions of HAVs, especially when it comes to properly conveying their intentions to human road users. Additionally, social sciences include critical components such as trust, social compliance and behavioural adaptability.

In general, a year restriction was set while conducting the research of relevant papers and it was decided that the year spectrum to be limited from 2016 and onwards. This was decided as HAV-related issues were emerging and as such the most recent papers had to be selected.

However, there were some cases where this restriction was violated and this was due to the paper's relevance to the topic. With respect to the risk of bias, while conducting this research, it was decided to examine various relevant sources in order to limit this possibility.

Tables 1 and 2 provide a concise overview of this search strategy:

***Table 1**: Search combinations for cyclists as VRUs*

<table>
<tr><th>Central keywords - 1st tier</th><th>Central keywords - 2nd tier</th><th>Auxiliary keywords</th><th>ScienceDirect results</th><th>Scopus results</th></tr>
<tr><td rowspan="6">Vulnerable road users, VRUs</td><td rowspan="6">autonomous vehicles, automated vehicles, AV, AVs, self-driving vehicles</td><td>perceptions</td><td>978</td><td>14</td></tr>
<tr><td>receptivity</td><td>86</td><td>1</td></tr>
<tr><td>acceptance</td><td>666</td><td>15</td></tr>
<tr><td>trust</td><td>924</td><td>11</td></tr>
<tr><td>expectations</td><td>506</td><td>5</td></tr>
<tr><td>interaction</td><td>1365</td><td>49</td></tr>
<tr><td rowspan="6">Cyclists, bicyclists</td><td rowspan="6">autonomous vehicles, automated vehicles, AV, AVs, self-driving vehicles</td><td>perceptions</td><td>629</td><td>7</td></tr>
<tr><td>receptivity</td><td>88</td><td>-</td></tr>
<tr><td>acceptance</td><td>380</td><td>2</td></tr>
<tr><td>trust</td><td>334</td><td>2</td></tr>
<tr><td>expectations</td><td>274</td><td>7</td></tr>
<tr><td>interaction</td><td>693</td><td>39</td></tr>
</table>

***Table 2**: Search combinations for social compliance of HAVs*

<table>
<tr><th>Central keywords</th><th>Auxiliary keywords</th><th>ScienceDirect results</th><th>Scopus results</th></tr>
<tr><td rowspan="4">autonomous vehicles, automated vehicles, AV, AVs, self-driving vehicles</td><td>social compliance</td><td>1619</td><td>16</td></tr>
<tr><td>driving style</td><td>1575</td><td>249</td></tr>
<tr><td>intentions</td><td>1729</td><td>444</td></tr>
<tr><td>behavioural adaptation</td><td>3977</td><td>50</td></tr>
</table>

Using the previously mentioned keywords as a starting point, a similar procedure was carried out on Google Scholar. It is remarkable that in the case of Google Scholar, the search results produced a substantially higher number of articles. As a result, more information was compiled than what was initially necessary. It is also worth noting that there were cases where the so-called "snowballing" method was applied when the corresponding scientific paper seemed to provide a better insight into certain information. In general, the choice of the literature was made based on a set of criteria, which in some cases prioritised the significance of the paper's title; while others considered the content. It is also crucial to note that all of the sources were openly accessible.

2.2. Cyclists as vulnerable road users

Cycling serves as a significant mode of transportation, especially in metropolitan areas. According to Ngwu et al. (2022), it refers to the use of non-motorised two-wheel transport. Cyclists, like pedestrians, fall under the category of VRUs within the road transportation system. They share the common characteristic of travelling with relatively minimal protection compared to the occupants of AVs or human-driven vehicles (HDVs). Nevertheless, cyclists exhibit distinct eye-gazing behaviour from pedestrians, as they concentrate more on the road ahead and conduct fewer shoulder checks (Berge et al., 2024). The concept of VRUs, which has gained prominence in the field of transport and road safety according to Reyes-Muñoz & Guerrero-Ibáñez (2022), originally emerged in the 1950s to describe unprotected road users. Therefore, several researchers have directed their focus toward enhancing the safety of these road users (Rahman et al., 2023). At this point, it would be useful to define the VRU term. The Intelligent Transportation Systems (ITS) Directive, defines VRUs as non-motorised users of the road, including cyclists, pedestrians, motorcyclists and individuals with disabilities or limited mobility and orientation (European Commission, 2015).

Navigating through congested city traffic poses one of the most significant challenges for autonomous vehicles, particularly in their interactions with vulnerable road users like cyclists, whose behaviour is inherently unpredictable (Berge et al., 2022). For that reason, several solutions have been suggested. Specifically, one suggested solution is to integrate human-machine interfaces (HMIs) that can display messages and notifications to both VRUs and AVs (Berge et al., 2023). Another strategy is to use external human-machine interfaces (eHMIs) that send cues to other drivers through lights, projections or displays. To enhance communication between VRUs and AVs, research on eHMIs has examined both structural elements (e.g., colour, form, placement) as well as component elements (e.g., text, symbol, illumination) (Berge et al., 2023).

2.2.1. Cyclists' perception of automated vehicles

In urban settings, cycling entails managing a considerable mental load and presents difficulties in predicting the behaviour of other road users, with cyclists in groups often prioritising group dynamics over attentiveness to motorised traffic (Berge et al., 2022). Recent studies underline the significance of understanding how VRUs perceive and interact with AVs, given the implications for road safety. First and foremost, tragic occurrences of VRU fatalities involving AVs highlight the need to grasp VRUs' perspectives and safeguard their interests in AV testing (Xing et al., 2022b). Furthermore, it has become apparent that there are age-related variations in safety perceptions, with older VRUs (aged 65 and above) expressing more significant safety concerns when sharing the road with AVs in comparison to younger adults (25-44 years). This aligns with previous research indicating that younger individuals exhibit more enthusiasm for AVs and fewer safety apprehensions (Xing et al., 2022a). In addition, the operation of AVs on public roads during pilot tests has raised safety concerns for VRUs, a thing which highlights the vulnerability of pedestrians and cyclists due to their lack of protection compared to AV occupants or conventional vehicle users (Rahman et al., 2021). Moreover, due to differences in their visual attention patterns, cyclists are often considered more vulnerable than pedestrians, as they typically prioritise the road ahead, potentially leading to reduced attention to passing vehicles (Berge et al., 2023). Positive information regarding AV behaviour has been shown to cause observable changes in people's perception, including accepting smaller gaps and maintaining shorter headways (Soni et al., 2022).

in order to protect VRUs and make sure AVs are successfully integrated into the road system, it is critical to take into account the concerns and differences in perceptions that exist among them. Before shedding light on cyclists' perceptions of AVs, it is first important to define the notion of perceived safety. Perceived safety constitutes the subjective assessment of risk encountered by users (He et al., 2022). In instances where perceived risk is low, individuals tend to feel relaxed, certain and comfortable, while higher risk perceptions lead to cautious behaviours such as increased vigilance and wariness (He et al., 2022). It is noteworthy that safety is regarded as a more widespread concern among users than an expected benefit (Gkartzonikas & Gkritza, 2019).

An interesting study was conducted by Berge et al. (2022), which examined the perceptions of cyclists regarding AVs. More accurately, cyclists foresee the continuation of current traffic ambiguity into the future, a thing which implies the incorporation of human biases and attitudes into AV algorithms, while they also seem to express a preference for AVs to mimic human behaviours and respond to sudden movements. Additionally, many of the respondents to this research believed it was the role of AV to guarantee the safety of other road users and especially that of cyclists. Another interesting aspect was that participants expected the AVs to be interconnected, sharing crucial data with rest road users and infrastructure. Moreover, cyclists expressed worries about their trust in interacting with AVs in mixed traffic situations and emphasised the need to be detectable by AVs while navigating.

This topic requires not only an awareness of how the general public views AVs but also a thorough investigation of how VRUs see them, which includes a range of positive expectations, concerns and attitudes (Xing et al., 2022a). The way that cyclists view AVs indicates a complicated structure of interrelated elements that affect how comfortable or nervous they are about sharing the road with this technology. According to Ngwu et al. (2022), cyclists express greater comfort while coexisting with AVs and strongly believe that the implementation of AVs will decrease crashes involving bicycles, lower the severity of crashes and improve the amount of road space available for cyclists.

Different people have different perceptions about cycling close to AVs. The latter is in accordance with a study that took place in 2015 and was conducted in the Phoenix metropolitan area of Arizona. More specifically, through this research, it was found that cyclists perceived cycling near AVs as the least safe activity when compared to driving or walking near self-driving vehicles (Pyrialakou et al., 2020). It is noteworthy that perceived safety stands as an essential human requirement and its adoption is influenced by awareness of the technology, socio-demographic factors and also country-level variables (Nordhoff et al., 2020). Generally speaking, VRUs' safety perceptions are influenced by their exposure to AVs. Those with greater exposure to AVs, regularly share the roads with them and pay more attention to AV-related news, tend to have higher perceived safety levels (Penmetsa et al., 2019; Rahman et al., 2023). Furthermore, safety perceptions are affected by factors such as support for AV vehicle testing on public roads, where support for AVs is positively correlated with perceived safety, while disapproval is negatively correlated, thus implying the fluid nature of public opinion around AVs (Rahman et al., 2023).

2.2.2. Cyclists’ acceptance & trust of highly automated vehicles

The development and implementation of AVs significantly depend on understanding public perception (Hulse et al., 2018). Recent studies have explored cyclists' receptivity to AVs, aiming to understand their interactive experiences (Xing et al., 2022b). To better understand this concept, it is essential to clarify the term “receptivity”. Smith (1988) defined receptivity as the willingness to embrace new technology, even in the face of uncertainty, unfamiliarity or paradox. Additionally, opinions on AVs may shift over time, particularly as people get more accustomed to the technology (Xing et al., 2022b). Furthermore, to capture VRUs’ receptivity, various virtual reality (VR) studies based on the scenario of crossing the road in front of AVs have been conducted. Examples of these experiments include the studies by Rad et al. (2020) and Nuñez Velasco et al. (2019).

Li et al. (2023) conducted a study that revealed how demographic factors impact cyclists' willingness to share the road with Fully Automated Vehicles (FAVs). The findings indicated that older individuals are generally less inclined to ride alongside FAVs compared to their younger counterparts, resulting in lower ratings across various factors, including attitude, trust, system effectiveness and compatibility. Similarly, male cyclists also exhibited reduced receptivity towards FAVs for similar reasons. These observations align with prior research, emphasising that males tend to have higher expectations regarding the suitability of FAVs for road sharing. Additionally, Xing et al. (2022b) carried out a study intending to shed light on the interaction of VRUs with AVs by comparing the 2017 and 2019 Pittsburgh surveys. Through this research, it was found that interactive experiences with AVs had a positive impact on VRUs’ receptivity and perception in general. However, the introduction of AVs to Pittsburgh did not result in a significant shift in overall receptivity.

The importance of user acceptance, a term which is similar to receptivity, has received a lot of attention in the context of self-driving cars. Nordhoff et al. (2020) emphasise the importance of safe and efficient interactions between AVs and VRUs for the effective deployment and integration of AV technology. In-depth investigations into public acceptance of AVs have been facilitated through questionnaire studies, a method commonly used in research (Nordhoff et al., 2019). However, Nordhoff et al. (2019) point out a limitation of such studies, stating their tendency to provide only surface-level insights. To address this, Venkatesh et al. (2003) proposed the so-called Unified Theory of Acceptance and Use of Technology (UTAUT), which argues that the desire to adopt technology is influenced by multiple factors, including performance expectancy, social influence and facitlitating conditions. This theoretical framework provides an overview of the challenges that are associated with the acceptance of technological innovations such as AVs.

Additionally, trust plays a crucial role for the successful adoption of automated driving (Stapel et al., 2022). According to Lee & See (2004), trust is a complex concept that may be interpreted as an attitude, intention or behavioural result. It may be an expectation of favourable responses or a willingness to act. In general terms, trust refers to one party’s willingness to expose oneself to the acts of another party with the expectation that the latter will perform a certain task required by the trustor (He et al., 2022). When it comes to automation, trust is characterised as the inclination of a user to be susceptible to the actions of an automated system (Körber et al., 2018). Papadimitriou et al. (2020) defined trust as an expectation that an automated agent will help an individual achieve their goals in unpredictable and vulnerable situations. It is impacted by contextual factors, such as task difficulty and perceived risks, a thing which highlights the need to take these factors into consideration (Ekman et al., 2021). High trust in autonomous driving is associated with more experience and may be impacted by individual characteristics, external or internal situations, as well as system performance (He et al., 2022). Conversely, excessive reliance on automation can result in misuse or complacency, thereby reducing monitoring performance (Stapel et al., 2022).

2.2.3. Expectations and interaction of cyclists with highly automated vehicles

In mixed traffic scenarios where both cyclists and AVs coexist, particularly at intersections, complex interactions occur that impact traffic flow and safety, as noted by Reddy et al. (2022). Additionally, individual differences play a significant role in shaping the interaction between cyclists and AVs. According to Vissers et al. (2016), the lack of a “standard cyclist” prevents the development of common interaction protocols for AVs, which in turn impedes standardised algorithmic programming. Consequently, effective communication between VRUs and AVs is critical for avoiding crashes and preventing loss of life. AVs can react accordingly if they are aware of their intentions, whereas VRUs can respond positively if they are informed of AVs intentions (Reyes-Muñoz & Guerrero-Ibáñez, 2022). Studies in human-machine interaction have shown that when cyclists interact with machines, they typically demonstrate more rationalism and less emotional response (Liu et al., 2022).

Nordhoff et al. (2019) conducted an interview study that focused on respondents' anticipations of autonomous shuttles. According to the data, respondents had higher expectations of autonomy in terms of the shuttle’s responsiveness to obstacles and route finding. Furthermore, many participants were disappointed by the shuttle’s limited speed and also by the presence of a steward on board. Likely, the difference between respondents’ idealised expectations and the reality of the prototype can be attributed to media portrayals of AVs, since they often emphasise their capabilities and in turn affect people’s anticipations. Furthermore, as per Vissers et al. (2016), expectations play a crucial role in shaping road-user decision-making and behaviour. They also stated that road users can form their expectations based on factors like previous encounters and traffic regulations.

Regarding cyclists’ behaviour on AVs, Vlakveld et al. (2020) conducted an experiment to capture cyclists’ intentions. In this study, it was found that cyclists’ yielding patterns at intersections might yield to cars when they have priority, especially when approaching AVs. Furthermore, in the same study, it was also mentioned that communication from AVs has a considerable impact on cyclists’ willingness to yield, primarily when it indicates awareness and adherence to traffic rules. Similarly, Madigan et al. (2019) argue that VRUs tend to place more emphasis on increasing the separation between their paths and those of AVs.

Recent field studies have provided insight into how other traffic participants adjust to the presence of AVs. Notably, drivers have a stronger propensity to accept gaps in front of AVs, which impacts gap acceptance behaviour at unsignalised intersections. This behavioural adaptation results from various factors, including AV appearance, driving style and driver attributes like age and gender. While drivers generally accept narrower gaps when merging in front of AVs compared to HDVs, no significant differences emerge concerning AV driving styles, recognisability, age or gender (Soni et al., 2022; Reddy et al., 2022). However, the combined effect of AV recognisability and driving style matters, favouring aggressive AVs, which leads to the acceptance of larger gaps. Critical gap measures, which are important for ensuring traffic safety, also show variation as a result of AV-related factors, highlighting the complex nature of interactions between humans and AVs, particularly in difficult situations like left turns. Road authorities have to carefully assess potential behavioural changes when teaching AVs to preserve critical traffic efficiency and safety as they contemplate infrastructure-to-vehicle (I2V) communication (Reddy et al., 2022).

2.3. Social compliance of highly automated vehicles

In a road environment, social interaction among various participants, including pedestrians, cyclists and drivers, is commonplace, involving communication, coordination, and occasionally, competition (Liu, 2023). Researchers have taken an interest in this issue, with Markulla et al. (2020) explaining that interactions on roads occur when the behaviours of two or more users are influenced by the likelihood of occupying the same space simultaneously. Similarly, when AVs integrate into mixed traffic, comparable circumstances emerge. During the initial testing phases by major technology companies such as Google, concerns were raised in media reports regarding the potential for AVs to become targets of aggressive driving or harassment (Liu, 2023).

Experts have also worked on defining socially compliant driving, each highlighting different parts of the concept. According to Schwarting et al. (2019), socially compliant driving involves behaving predictably in interactions with both human and autonomous agents, especially in various social dilemmas. Vinkhuyzen and Cefkin (2016) describe socially compliant autonomous driving as how AVs operate during specific traffic interactions. More accurately, AVs are anticipated to achieve a balance, avoiding both aggressive behaviour and excessive yielding to other road users, with the ultimate goal of seamlessly integrating into traffic flow without causing disruptions. Although self-driving technology has the potential to increase road safety and convenience while relieving people of driving duties; achieving those benefits depends on securing social acceptance (Ma & Zhang, 2021). In essence, socially compliant driving of AVs calls for the replication of human-like behaviour and adherence to social standards to increase safety for both passengers and other road users (Schwarting et al., 2019).

2.3.1. Driving style of automated vehicles

Driving styles in AVs appear to have a wide range of characteristics and behaviours that decisively influence acceptance, trust and takeover behaviours. These driving styles demonstrate automated skills and consistent behaviours displayed by drivers in a variety of driving circumstances (Ma & Zhang, 2021). However, even though there is consensus about the significance of driving style, there is disagreement regarding its conceptualisation and measurement (Taubman-Ben-Ari et al., 2004). Driving styles tend to reflect individual preferences and habits that are related to speed and overtaking decisions; while they appear to show stable characteristics for each driver. More precisely, to operationalise these driving styles, specific behaviour indicators are used that cover aspects like speed, acceleration, time headway, steering, gap acceptance and compliance with the rules (Bellem et al., 2018). In general, defensive driving prioritises safety with lower speeds, smoother acceleration, early deceleration and wider spaces; while aggressive driving favours speed, tailgating, jerky driving, high flashing lights and honking (Ma & Zhang, 2021).

Another tool which is used to describe driving style is the so-called Social Value Orientation (SVO). According to Buckman et al. (2019), SVO is a metric that derives from social psychology and serves as a tool to quantify human personalities by assessing how individuals balance personal rewards with rewards for others. More specifically, this classification system captures individual tendencies towards various social preferences, including attitudes towards altruism, fairness, reciprocity, inequity aversion and egalitarianism (Schwarting et al., 2019). Hence, if the SVO of an agent tends to be more prosocial, this means that it prioritises the other agent’s reward, thus increasing the likelihood of yielding. Understanding another agent's SVO allows an AV to more accurately anticipate their behaviour, which helps determine whether to proceed with a turn based on expected cooperation (Schwarting et al., 2019). Also, anthropomorphism is a characteristic that tends to boost people’s trust and is often used in interactions between machines and individuals. Oliveira et al. (2019) assert that people prefer robots that demonstrate human-like behaviours because they provide a feeling of social presence and boost perceptions of safety, intelligence and trustworthiness in AVs.

It becomes obvious that driving styles exert a significant influence on trust regarding AVs (Ekman et al., 2021). However, different styles of AVs can lead to inconsistent behaviour, which defies the expectations of other traffic participants. This inconsistency is partly due to the lack of standard concepts of ethical and safety behaviour in machines (Papadimitriou et al., 2022). Furthermore, according to research, people whose driving styles are compatible with the AV's driving style have a substantially higher level of trust in the AV systems (Ma & Zhang, 2021). Additionally, increased confidence in AV technology is associated with maintaining a central lane position (Sun et al., 2023). It is worth noting that, in general, "defensive" driving styles are more trusted than "aggressive" ones because they are more predictable. (Ekman et al., 2021).

2.3.2. Communicating intentions of highly automated vehicles

Another important aspect which shapes cyclists' opinion on AVs is the way these two agents communicate in real-traffic conditions. Berge et al. (2023) categorised communication types into four main categories: a) visual, b) auditory, c) motion-based and d) wireless. Cyclists frequently face plenty of obstacles (e.g., parked cars, vehicles stopping and starting in bicycle lanes, etc.) because of other road users' unpredictable actions (e.g., rule violations, sudden braking, etc.) (Berge et al., 2022). Hence, the way AVs convey their driving intentions to other road users in a distinct and understandable manner is one of the most significant challenges facing this technology (Miller et al., 2022).

According to Harkin et al. (2023), researchers are divided on the issue of communicating driving intentions. Some advocate for explicit communication, while others lean towards implicit methods. The definition of implicit communication (i.e., kinematic behaviours), according to Markkula et al. (2020), is a road user's behaviour which impacts their own movement or perception but may also be viewed as a signal to or a request from another road user and continues to exist even when road users are ignorant of its existence (Mohammadi et al., 2023). With respect to explicit communication, it refers to acts or behaviours that are perceived as signalling or demanding something from another road user (e.g., hand gestures, headlight flashes, etc.), although they do not immediately affect their own movement or perception (Markkula et al., 2020; Mohammadi et al., 2023). According to Berge et al. (2022), cyclists anticipate effective detection and prefer AVs to communicate explicitly throughout exchanges.

Interactions between manual drivers and AVs in mixed traffic conditions can create particular difficulties, as AVs often behave differently and adhere strictly to restrictions like speed limits (Van Loon & Martens, 2015). AVs could experience difficulties with understanding as a result of not comprehending unwritten social road norms (Stange et al., 2022). Hence, communicating the intent of AVs is a critical aspect of ensuring safe and effective interactions between them and human road users. It is crucial to create simple and understandable ways for AVs to communicate their intentions to other traffic participants on the road, whether they are stopping, moving or preparing to take action. This is especially true as AV technology continues to advance (Vinkhuyzen & Cefkin, 2016). External human-machine interfaces (eHMIs) can play a vital role in conveying information over driving interactions.

As per Schieben et al. (2018), these interactions can be divided into four key categories, namely:

1. ***Driving Status Information***: This category informs road users of the AV's current automation status and raises awareness of its operational mode.
2. ***Future Manoeuvre Information***: This classification provides information about the AV's upcoming behaviours, enabling others to anticipate its moves and make well-informed preparations.
3. ***Perception of Environment***: Here it is indicated if the AV has recognised the presence of nearby road users, ensuring that others are informed of their detection.
4. ***Cooperation Capabilities***: This category examines how well the AV cooperates with other road users in various traffic scenarios, indicating its ability to interact harmoniously.

Although eHMI is a promising communication tool for safe interaction between AVs and other traffic participants, the potential for misunderstandings must be considered (Wilbrink et al., 2021).

Cefkin et al. (2019) initiated a research programme to explore interactions with AVs and their impact on the road. AVs exhibit distinct kinematic cues, posing challenges in micro-negotiations during interactions. To address this, the "Intention Indicator" was introduced, a novel communication signal designed to effectively convey an AV's operational state in three conditions: stopping or stopped, going and about to go. This signal is visible from all angles to promote road safety and understanding. The simulation study found that at four-way stop crossroads with multiple AVs, the "Intention Indicator" could improve traffic flow, particularly if its use becomes more familiar to road users. The researchers suggested several enhancements for the "Intention Indicator" system: avoiding complex symbols, using discrete signal states for easy perception, adhering to international colour standards and ensuring visibility at eye level for other traffic participants (Cefkin et al., 2019).

According to De Winter and Dodou (2022), automated driving creates a "social interaction void" due to the absence of the human driver, a thing which makes imperative the use of eHMIs for VRU communication. In addition, human factors experts caution against instructive eHMIs to prevent accidents and misunderstandings (Dey et al., 2022), whereas others advocate for text-based eHMIs for direct understanding. Berge et al. (2022) studied AV-cyclist interactions and found that cyclists prefer explicit recognition and communication from AVs, favouring HMI features that enhance connection with drivers and provide location information. Despite over 70 proposed eHMI concepts, comprehensive evaluations are lacking. For instance, green and red front brake lights are suggested as alternatives, with green indicating safe crossing and red showing the AV cannot proceed from a pedestrian's perspective. Vulnerable road users generally prefer an egocentric viewpoint, making them more inclined to cross in front of green eHMIs (Bazilinskyy et al., 2021).

On the other hand, an alternative means to enhance interactions between AVs and cyclists is through on-bike HMIs, a topic explored by Berge et al. (2022). More accurately, cyclists are considering these interfaces, with a particular emphasis on functions that offer information about the position of other road users and promote communication amongst road users. However, it is argued in the same study that cyclists appear to be hesitant to embrace them due to doubts about their practical utility and ethical concerns about possibly transferring safety responsibility to the more VRU.

2.3.3. Behavioural adaptation of automated vehicles

The subject of behavioural adaptation concerning automated driving is of interest to the transport-related scientific community. Therefore, defining this aspect would be helpful. According to Rudin-Brown & Jamson (2013), behavioural adaptation includes any change in a driver's or traveller's behaviour that occurs after interacting with a change to the road traffic system. This includes both the behaviours that the change's initiators intended to influence and other unintended shifts in behaviour.

Subsequently, the adoption of AVs has been accompanied by both optimism and scepticism. Schwarting et al. (2019) argue that AVs exhibit conservative driving behaviour, which may lead to traffic bottlenecks and misunderstandings. This cautious approach, especially at intersections and left turns, increases vulnerability to human aggression and reduces their clarity of intentions, leading potentially to a significant portion of AV crashes.

Moreover, some experts doubt if the assumptions and logic used to understand how both human drivers and AVs behave are accurate, questioning whether AVs will actually make driving safer as predicted (Liu, 2023). Therefore, this complicated situation, along with many people not having much experience with this new technology, makes it hard to understand what AVs are doing, thus pointing out the need for additional research and development efforts to connect with public expectations.

2.4. Main findings

In this literature review, two major elements were examined: a) cyclists as VRUs and b) social compliance in HAVs. Cycling, a vital mode of urban transportation involving non-motorised two-wheel transport, categorises cyclists as VRUs due to their lack of protection compared to vehicle occupants. Cyclists prefer HAVs that mimic human behaviours and protect the safety of all road users, especially cyclists. Despite these expectations, there are still worries about trusting HAVs in mixed-traffic situations and the significance of being visible when navigating.

Nevertheless, cyclists generally express a higher level of comfort coexisting with HAVs, believing in their potential to reduce bicycle-related crashes and enhance road availability for cyclists. However, perceptions of safety among cyclists remain a critical concern which is influenced by factors such as familiarity with the technology and socio-demographic variables. Furthermore, receptivity, user acceptance and trust are crucial factors which shape the perceptions and behaviours of cyclists regarding HAVs. Precisely, receptivity is affected by familiarity, evolves over time and impacts overall opinions on HAV technology. User acceptance is essential for HAV deployment and is determined by factors such as performance expectancy and social influence.

Trust, on the other hand, is characterised by vulnerability to AV actions and is also influenced by contextual factors and individual characteristics. Moreover, in mixed-traffic environments, particularly at intersections, the complex interactions that unfold between cyclists and HAVs are further complicated by individual differences among cyclists, making it challenging to establish standardised protocols. Effective communication emerges as a vital component in navigating these interactions and avoiding accidents. HAVs must respond appropriately when cyclists' intentions are attuned, emphasising the need for clear communication channels between HAVs and cyclists.

In addition to the need for effective communication, the driving styles of HAVs also significantly impact the acceptance and trust of these vehicles. Additionally, anthropomorphism enhances trust by attributing human-like behaviours to HAVs. Trust levels increase when individual driving styles align with HAV behaviour, with defensive styles generally receiving more trust due to their prioritisation of safety and predictability.

Moreover, the use of eHMIs plays an important role in conveying essential information, such as driving status and future manoeuvres and contributes to predictability and by extension to road safety. However, opinions diverge on eHMI design principles, with debates over instructive versus explicit communication. Innovations like the "Intention Indicator" aim to enhance predictability, especially at complex intersections. Yet, concerns persist about the practicality and ethical implications of eHMIs, particularly regarding the transfer of safety responsibility onto VRUs.

Despite the considerable amount of research conducted on how HAVs adapt their behaviour and their driving styles, there is still a significant gap in understanding how cyclists perceive and react to HAVs' driving behaviour and communication strategies, especially at unsignalised intersections and shared roadways. Therefore, this literature review identifies the need for comprehensive research that investigates cyclists' perspectives on HAVs' adoption of a socially compliant driving style to enhance trust and perceived safety in mixed-traffic environments. This gap will be addressed in this study through the development of a conceptual model in Chapter 4.1, which will serve as the foundation for subsequent statistical analyses aimed at bridging this research gap and facilitating the integration of HAVs into urban transportation systems while ensuring cyclist safety and acceptance.

3. Methodological approach

This chapter's goal is to provide a practical research approach that will be able to produce the necessary results needed to address the research question and its related sub-questions as posed in Chapter 1.3. A brief definition of a research approach might be helpful at this point. According to Jansen and Warren (2023), a research methodology is the answer to the practical "how" of any piece of research. It is connected to the prospective way of conducting a study that will be carried out in order to deliver reliable and accurate results that fulfil the requirements of the research. In this case, a combination of qualitative and quantitative research methods will be employed.

3.1. Research and survey design

As previously mentioned, the conceptual framework was developed based on data gathered from a literature review and interviews with three professors and one PhD student at Delft University of Technology. The selection of these professors was based on their academic expertise and relevance to the research topic, specifically cyclist-HAV interactions. These experts were approached due to their extensive background in this field and their numerous publications on cyclists' acceptance, perceived safety and receptivity towards HAVs. Their selection was purposeful, as each could provide insights from different perspectives, including behavioural, safety, biomechanical and intelligent vehicle aspects.

During the interviews, the professors were asked about their experience with cyclist behaviour and their definitions of the socially compliant behaviour of HAVs. They were also asked to recommend any relevant studies and to identify the most important factors affecting socially compliant behaviour, explaining their reasoning for these choices. Additionally, the professors were consulted on the completeness of the conceptual framework, specifically regarding the design variables and factors included and whether there were any omissions in the initial conceptual framework that was presented to them. They were also asked to assess the correctness of the relationships between the design variables.

An initial, simplistic common framework was consequently created for all participants to draw more reliable conclusions. Then, through this iterative process, each expert's contributions helped to develop a more robust and scientifically sound conceptual model which includes all essential information (see Chapter 4.1.).

Subsequently, a survey was developed based on the conceptual model. The goal was to create various traffic scenarios to examine how cyclists' trust, perceived safety, and perceived social behaviour of HAVs, as well as their intended actions (dependent variables), are influenced by certain factors (independent variables). These independent variables include the driving dynamics of HAVs (i.e., speed and direction), the communication of HAVs' intentions, specific demographic factors (i.e., gender, age group and level of education), frequency of cycling and familiarity with AVs, either as a passenger or driver.

Consequently, the thesis was structured to collect all necessary data, thereby facilitating subsequent statistical analysis.

3.2. Participants recruitment

The criteria for participation in the survey were established to target individuals residing in the Netherlands, aged 18 and above, with a minimum target of 50 respondents. To meet these criteria, a convenience sampling approach was adopted, primarily reaching out to friends, lecturers and acquaintances residing in the Netherlands. Additionally, recruitment efforts were extended to include fellow students via WhatsApp groups, as well as associations dedicated to cyclists. The survey was published on Microsoft Forms and was also uploaded on SurveyCircle, an online platform designed to facilitate the promotion of student surveys. Through these channels, the survey successfully attracted participants who met the previously mentioned criteria, thus contributing to the attainment of the desired sample size for the study, totalling 76 participants.

3.3. Data collection and analysis

The survey recruitment received approval from the Human Research Ethics Committee of Delft University of Technology in March 2024 (reference no. 3888). The survey was conducted for three weeks, namely from March 13th to April 3rd 2024. At the beginning of the survey, an introductory statement was included to provide all the necessary information to participants. Additionally, participants were assured that their responses would remain confidential throughout the survey process, ensuring anonymity. Further, participation in the survey was entirely optional and participants were free to withdraw from the survey at any time without facing any consequences.

Regarding the data analysis, the main research question, as mentioned in Chapter 1.3., is:

> ***Main Research Question:*** *What factors do cyclists consider important for the social driving behaviour of HAVs?*

To shed light on different aspects of the main research question, four sub-questions will be addressed.

> ***Sub-question 1****: What are the conceptual determinants of socially compliant driving behaviour?*

The methods for addressing this Sub-question include a literature review and expert interviews with professors from Delft University of Technology. Through this procedure, a conceptual model was developed to visually depict the relationship among various elements that are involved in the cyclist-HAV interaction. Chapter 4.1. provides a detailed presentation of the conceptual framework.

> ***Sub-question 2****: Under which conditions do cyclists perceive a HAV to drive in a social manner?*

For Sub-question 2, a descriptive analysis of the survey was employed, based on the data received from the online survey. Chapter 4.2. meticulously describes the steps taken in order for this sub-question to be addressed.

> ***Sub-question 3****: Which factors influence cyclists' perceptions and expectations of HAVs regarding Trust, Perceived Safety and Perceived Social Behaviour?*

At first, non-parametric correlation tests (bivariate correlation) are used for each dependent variable (i.e., Trust, Perceived Safety and Perceived Social Behaviour) to explore which variables have a strong correlation with them. Following that, a Repeated Measures Analysis of Variance (ANOVA) was applied to each dependent variable (i.e., Trust, Perceived Safety and Perceived Social Behaviour). This test aims to identify any statistically significant differences in means among the levels of the dependent variables subjected to the influence of input variables such as Demographics and HAV-related statements. In Chapters 4.3.1. and 4.3.2. both processes are described.

> ***Sub-question 4:*** *Do Trust, Perceived Safety and Perceived Social Behaviour affect the cyclists' intended behaviour? If so, what other factors might also influence this intended behaviour?*

Statistics offers a method to examine and analyse the impact of various variables, known as independent variables, on a decision variable characterised by different levels (categories). This decision variable acts as the dependent categorical variable. Multinomial Logistic Regression applies in situations like this. The dependent variable will be the cyclists' reaction. It is a categorical variable with three levels namely, “Brake”, “Decelerate” and “Continue cycling at a constant speed”. The independent variables will be Trust, Perceived Safety, Perceived Social Behaviour, respondents' Familiarity with AVs, Age Group of participants and their Experience either as a passenger or a driver with AVs. All of the independent variables are of nominal/ordinal type since they are Likert scaled. Chapter 4.3.3. describes the assumptions, the theoretical foundations and the exact steps taken to conduct this statistical test.

3.4. Traffic scenarios selection and design

In this survey, special attention is given to the interaction between cyclists and HAVs within urban settings, particularly focusing on unsignalised intersections with non-dedicated and shared bicycle lanes. Berge et al. (2022) argue that cyclists favour segregated infrastructure, such as bicycle paths, over shared roadways and find signalised intersections less intimidating due to clearer traffic guidance. Hence, the selection of unsignalised intersections as the primary focus of analysis is motivated by their significance as common sites of traffic conflict and negotiation, which is particularly evident in mixed traffic conditions where HAVs and cyclists coexist. Therefore, within these intersections, challenges arise from the complex spatial arrangements and diverse user behaviours associated with non-dedicated and shared bicycle lanes.

Further, majority of bicycle-vehicle incidents occur when the vehicle approaches the cyclist perpendicularly (Berge et al., 2024). Therefore, each scenario was thoughtfully developed to present different driving conditions. Specifically, variations were introduced in the direction of the HAV (either perpendicular or moving in parallel with the cyclist), the clarity of the HAV's intentions (indicated through eHMI or left ambiguous) and the speed of the HAV (maintaining a constant speed, decelerating, accelerating or braking). This intentional variation made it possible to conduct a thorough investigation of the various aspects that potentially affect cyclists' perceptions and responses to HAV interactions in various urban environments.

Hence, the goal of the survey was to create various traffic scenarios involving cyclists and HAVs at unsignalised crossings and on shared roadways to examine how cyclists' trust, perceived safety, the perceived social behaviour of HAVs and cyclists' reactions, which constitute the dependent variables, are influenced by certain independent variables. These independent variables include the driving dynamics of HAVs (i.e., speed and direction), intention clarity of the self-driving vehicle, HAV speed, specific demographic factors (i.e., gender, age group and level of education), frequency of cycling and familiarity with AVs, either as a passenger or driver.

The survey, which can be found in full in Appendix A was divided into four sections, each of which was intended to provide insight into various aspects of respondents' views and opinions regarding self-driving vehicles.

- In the first part of the survey, demographic-related questions were asked in a multiple-choice format. In the following section, participants were first asked if they were familiar with the concept of socially compliant driving behaviour of HAVs.
- Next, they were asked an open-ended question to share their opinions on certain actions or behaviours that they felt contributed to socially compliant driving. To ensure unbiased responses, definitions of eHMI and socially compliant driving were provided after this section.
- Subsequently, eight Likert scale statements were included in the third section of the survey to allow respondents to indicate whether they agreed or disagreed with a variety of propositions about cyclists' attitudes and perceptions of HAVs. The rating scale ranged from 1 for strongly disagreeing to 5 for strongly agreeing.

The following are the eight statements presented to the respondents:

***Table 3**: Statements about participants' perceptions and attitudes towards HAVs*

Statement 1:	*"I trust autonomous vehicles to always prioritise the safety of bicyclists"*
Statement 2:	*"I believe that HAVs can effectively communicate their intentions to bicyclists"*
Statement 3:	*"I am confident in my ability to predict the intended behaviour of HAVs while cycling"*
Statement 4:	*"I would be comfortable sharing the road with HAVs in various traffic scenarios"*
Statement 5:	*"The use of electronic Human-Machine Interface (eHMI) by HAVs enhances my trust in their intentions"*
Statement 6:	*"HAVs are more likely to follow traffic rules compared to human drivers"*
Statement 7:	*"Predictable behaviour of autonomous vehicles is essential for socially compliant driving in mixed traffic environments"*
Statement 8:	*"I feel more comfortable sharing the road with autonomous vehicles when their driving behaviour is predictable"*

- In the last part, seven scenarios were created to assess individuals' Trust, Perceived Safety and Perceived Social Behaviour regarding HAVs using a Likert scale from 1 to 5. Additionally, they were asked to indicate their potential reaction to each scenario. Each scenario was presented in a sequential order and respondents were asked to provide their preferred responses.

In brief, the scenarios developed are outlined below, explaining why they were presented and what they aimed to explore.

Scenario 1: Deceleration at unsignalised intersection (clear deceleration, clear indication of HAV's intention)

This scenario supposedly took place at the Prinsessewal & Noordwal intersection and participants envisioned themselves cycling along a shared roadway to proceed straight, while the HAV approached the unsignalised intersection from a perpendicular/opposite direction. Here it should be noted that the HAV exhibited clear signs of deceleration and signalled its intent to yield. In this instance, the objective is to assess the impact of the HAV's clarity of intentions and its crossing in front of the cyclist on participants.

***Figure 3**: Graphical representation for Scenario 1*

Site Coordinates: 52°04'48.9"N 4°18'13.7"E

Scenario 2: Deceleration at unsignalised intersection (smooth deceleration, no clear HAV's indication of intention)

The setting for this scenario was the same as in Scenario 1, albeit with a minor modification. Here the HAV decelerates smoothly but the hypothesis is clear indicators are absent regarding its intentions at the intersection. Here, the aim is to investigate the extent to which these changes influence participants' perceptions.

Figure 4*: Graphical representation for Scenario 2*

Site Coordinates: 52°04'48.9"N 4°18'13.7"E

Scenario 3: Constant speed of an HAV driving parallel to a cyclist on a straight road

For this instance, the participants were asked to imagine themselves cycling along Parkstraat street, while an HAV maintained a constant speed alongside them.

Figure 5*: Graphical representation for Scenario 3*

Site Coordinates: 52°05'03.4"N 4°18'24.3"E

Scenario 4: Sudden acceleration of an HAV driving parallel to a cyclist on a straight road

In scenario 4, the setting was the same as in scenario 3, only with one minor modification: rather than maintaining a constant speed, the HAV abruptly accelerated. The aim was to investigate participants' perceptions when encountering unexpected behaviour from HAVs in a typical cycling environment.

Figure 6: *Graphical representation for Scenario 4*

Site Coordinates: 52°05'03.4"N 4°18'24.3"E

Scenario 5: Use of external Human-Machine Interface (eHMI) at intersections yielding priority to cyclist

Scenario 5 depicted a traffic situation at Parkstraat & Lange Voorhout intersection, where a cyclist navigates a non-dedicated bicycle lane adjacent to an HAV positioned on the right side aiming to make a left turn. It is noteworthy, that the HAV used an eHMI to signal its intention of prioritising the cyclist's path by stopping. The purpose was to capture participants' perceptions regarding external devices and their effectiveness in enhancing HAV-cyclist communication in shared environments.

Figure 7*: Graphical representation for Scenario 5*

Site Coordinates: 52°04'53.3"N 4°18'34.9"E

Scenario 6: Use of external Human-Machine Interface (eHMI) at intersections not yielding priority to cyclist

The setting in this scenario was the same as in Scenario 5. The difference in this instance, though, is that the HAV signals that it will not wait for the cyclist to pass and will instead pass through the intersection at a steady speed.

***Figure 8**: Graphical representation for Scenario 6*

Site Coordinates: 52°04'53.3"N 4°18'34.9"E

Scenario 7: Cyclist's response to HAV's deceleration when approaching from the opposite direction and turning left to continue alongside the cyclist

The final scenario took place at the Torenstraat & Noordwal intersection. Here, respondents were asked to imagine themselves navigating at an intersection to make a right turn, while the HAV approaches from the opposite direction. Additionally, the HAV decelerated to execute a left turn. The purpose, here, was to capture cyclists' perceptions and reactions when encountering HAVs manoeuvring at intersections.

***Figure 9**: Graphical representation for Scenario 7*

Site Coordinates: 52°04'46.3"N 4°18'11.0"E

4. Results

4.1. Conceptual determinants of socially compliant driving

Following discussions with experts and based on the read literature, the conceptual framework took shape as depicted in Figure 10 on the next page. To facilitate the analysis of individual elements, the framework was divided into two parts: the left part describes elements related to the functions and characteristics of HAVs, while the right part focuses on factors related to cyclists. Arrows within the framework indicate a flow of influence and interaction between different elements.

Specifically, it is assumed that driving style serves as the primary determinant within the HAV segment. This driving style dictates both the dynamics of driving, such as smooth or sharp acceleration/deceleration, defensive or aggressive driving and the communication of intentions. These elements, namely the dynamics of driving and the communication of intentions, are thus grouped under the driving style category. The bidirectional arrow signifies their interdependence, suggesting a reciprocal relationship where the dynamics of driving impact communication intentions and vice versa.

Following this, the general category of driving style is suggested to impact trust, perceived safety and perceived social behaviour of cyclists. It is also hypothesised that these three variables are interconnected, a conclusion drawn from both the literature review and interviews with experts. Moreover, it is suggested that the box which includes trust, perceived safety and perceived social behaviour is influenced by additional factors such as demographics, cycling frequency, familiarity with AVs and the cycling infrastructure (e.g., shared roadways or separated bicycle lanes). The arrows indicating the relationships from demographic factors to trust and from trust to perceived safety and perceived social behaviour, imply that demographic factors play a role in shaping a cyclist's trust in automated vehicles, subsequently influencing their perceptions of safety and social behaviour.

Additionally, it is assumed that the combined factors of trust, perceived safety and perceived social behaviour influence a cyclist's potential response to an interaction with an HAV. However, it is also speculated that the cyclist's intended behaviour could reciprocally impact the levels of trust, perceived safety and perceived social behaviour. It is also proposed that the cyclist's intended actions can influence the driving style of HAVs, thereby establishing a feedback loop between cyclists and AVs. This speculation arises from the capability of HAVs to adapt their driving behaviour based on sensor inputs. Notably, some experts questioned the notion of a feedback loop between HAVs and cyclists, viewing it as an interaction between a machine and a human. However, it is argued that the presence of sensors in HAVs bridges this gap, enabling the establishment of a feedback loop.

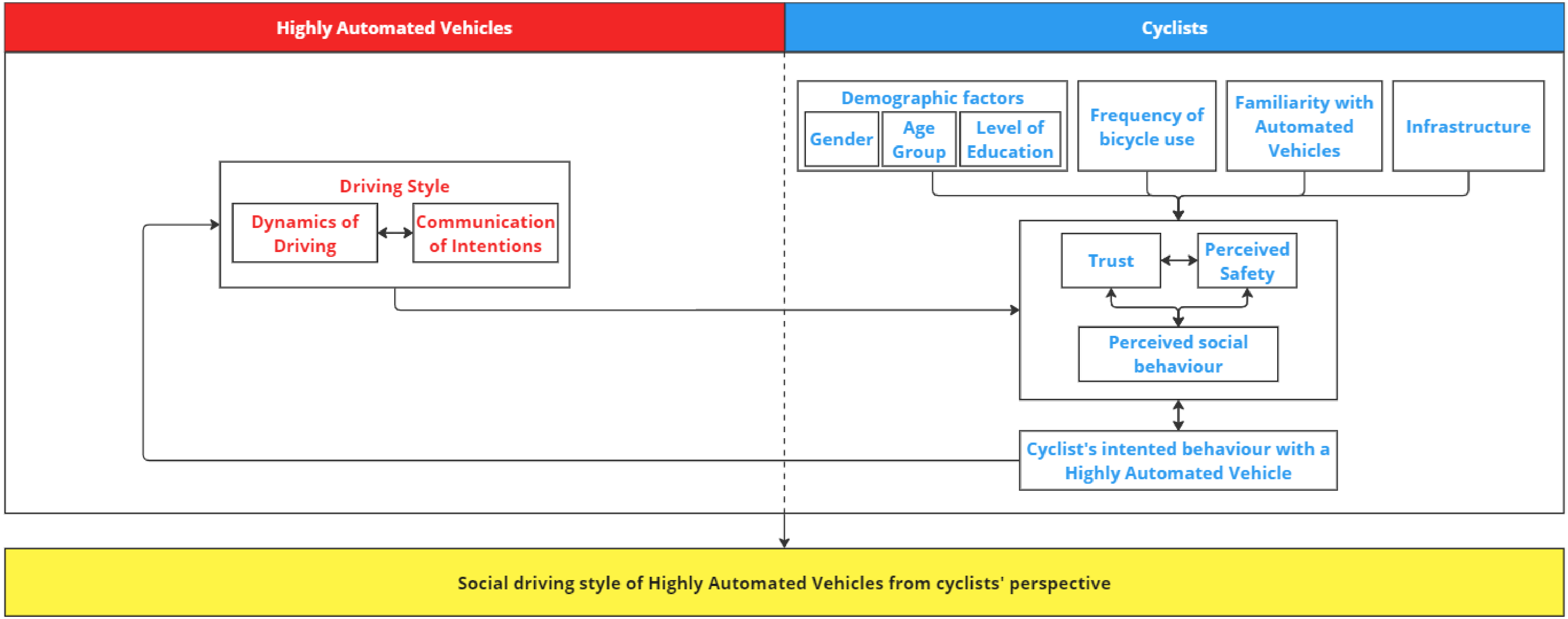


Figure 10*: Conceptual Framework of cyclist-HAV interaction*

4.2. Descriptive analysis of the survey

As mentioned in Chapter 3.2., the survey gathered responses from a group of 76 participants which was predominantly comprised of younger people, with over 60% being under 34 years old. This shows a large representation of people in their peak working and commuting years, which is likely to influence their attitudes towards urban mobility and self-driving vehicles. Additionally, it can be noticed that in this survey there is minimal representation of older groups. Subsequently, respondents' cycling frequency demonstrates a wide variety of engagement with the activity. Some 37% (n = 28) of the sample reported cycling on a daily basis. This shows that a significant proportion of participants are regular cyclists, indicating a group with a high preference for active transportation. In addition, 26% (n = 20) of respondents stated that they cycle several times per week, suggesting that a substantial number of people cycle frequently but not necessarily on a daily basis. In contrast, a noteworthy minority reported less frequent cycling habits. Almost 37% of the participants mentioned cycling less than once a week or even never. Consequently, this data illustrates an active cohort, with a small proportion engaging in minimal cycling activities.

Later in the analysis, it becomes evident that respondents have varying levels of exposure to automated vehicles (AVs). A significant portion (44.8%) acknowledged some familiarity or direct experience with self-driving vehicles, indicating moderate exposure within the sample. However, 27.6% reported no past engagement with AVs, showing that a sizeable portion is still unfamiliar with this technology. The remaining 27.6% demonstrated partial familiarity. Concerning the educational profile of participants, it reflects a well-educated group, predominantly holding Bachelor's and Master's degrees. Notably, there were no respondents with only high-school diplomas and only a very small number with technical/vocational training (n = 2), indicating a bias towards higher educational backgrounds. The high proportion of Doctoral degree holders further suggests a propensity for deeper engagement with complex subjects. While the lack of participants with lower educational qualifications may limit the generalisability of the findings, it also indicates a skew towards individuals with higher socioeconomic status and access to academic environments. Besides, respondents' familiarity with the concept of socially compliant driving varies. About 29% (n = 22) reported unfamiliarity with the concept, while 42% indicated a moderate to high level of familiarity.

Furthermore, an open-ended question where the respondents could express their opinion concerning the specific behaviours or actions by HAVs that contribute to socially compliant driving was posed. Here, several interesting viewpoints were expressed. More accurately, a significant amount of respondents focused on rule compliance and predictable driving, by stretching the importance of HAVs adhering to speed limits, yielding to cyclists and behaving in an understandable and consistent way. Moreover, several respondents expressed the view that safety and consideration for vulnerable road users are of utmost importance. Actions like giving priority to cyclists or adjusting driving behaviour were frequently referred by participants. Other elements that were often mentioned are the ethical considerations (e.g., danger evaluation, roadmanship) and the sensory systems like detection systems for cyclists and pedestrians.

Figure 11 on the following page summarises the findings grouped by gender, age group, frequency of cycling, experience with AVs, level of education and familiarity with the concept of socially compliant driving.

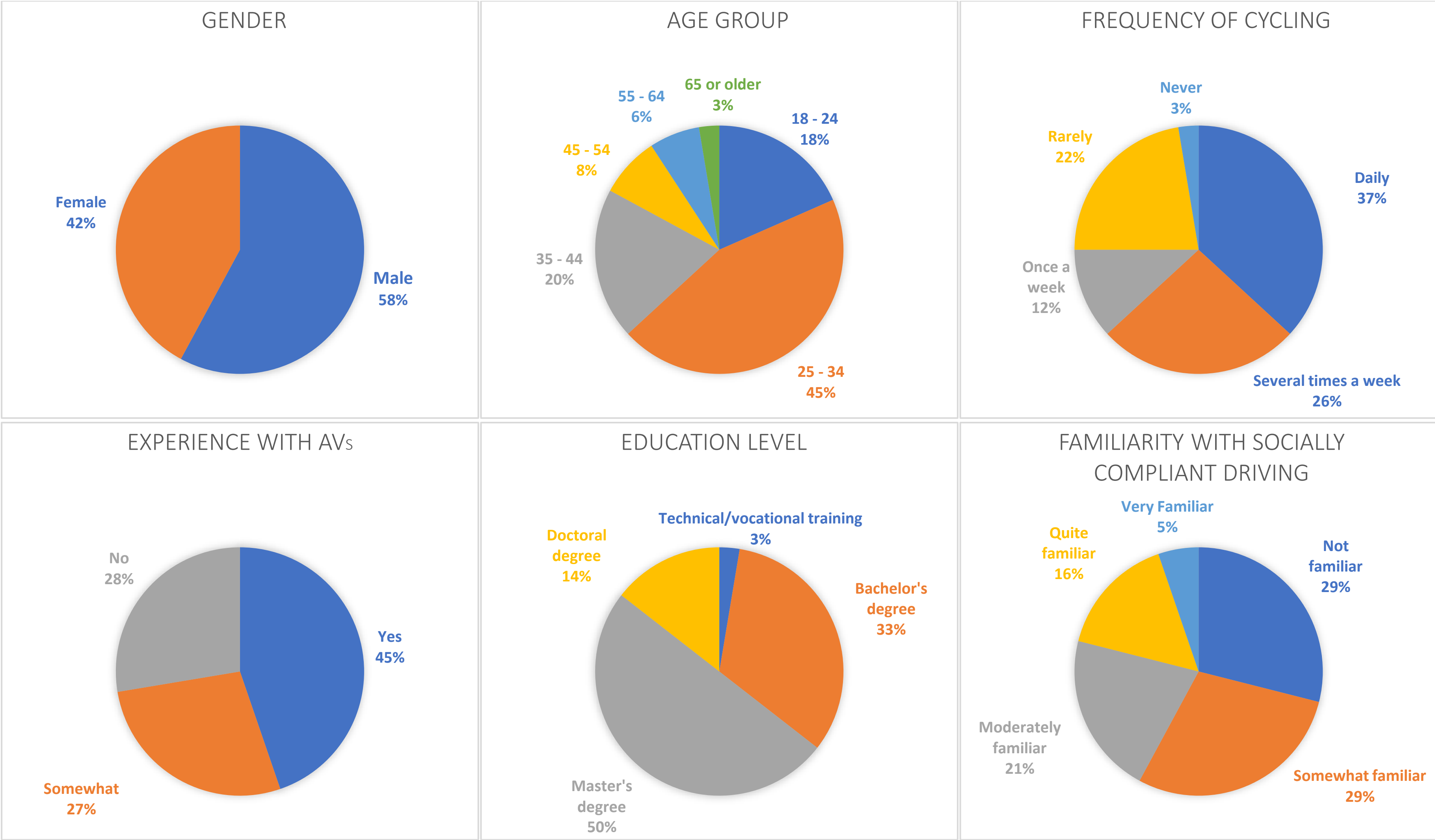


Figure 11*: Respondent characteristics and key elements of socially compliant driving*

Later, eight statements were posed for evaluation. From the results, it can be inferred that different attitudes and perceptions can be noticed among respondents. First, it should be mentioned that regarding trust in HAVs prioritising cyclist safety (Statement 1), the responses reveal a relative balance between positive and negative responses. This suggests a level of uncertainty among participants concerning safety prioritisation. Similarly, perceptions of HAVs' communication of intentions (Statement 2), confidence in predicting HAV behaviour (Statement 3) and respondents' comfortability in sharing the roads with HAVs (Statement 4) show a similar trend. With regard to Statement 5 (i.e., use of eHMI by HAVs), it can be noticed that it received predominantly positive responses, a thing which indicates that such interfaces tend to enhance trust in HAV intentions among cyclists. In the same fashion, Statements 6 (i.e., rule compliance of HAVs), 7 (i.e., the essentiality of predictable behaviour of HAVs in socially compliant driving) and 8 (i.e., cyclist's comfortability in sharing the road with HAVs when they drive predictably) also received overwhelming support.

Figure 12 illustrates the distribution of responses for Statements 1-8. The horizontal axis spans from 0% to 100%, representing the relative proportions of responses across Likert scale categories. A value of 0% indicates all responses lean towards the negative end of the scale (e.g., selecting 1, indicating strong disagreement), while 50% signifies a balanced distribution between positive and negative responses or where the midpoint of the scale (e.g., 3 on a 1-5 scale) is most common. A value of 100% shows all responses are on the positive end (e.g., selecting 5, indicating strong agreement). This axis clarifies how responses are distributed across negative, neutral and positive categories, with bars extending left indicating more negative responses and bars extending right indicating more positive responses.

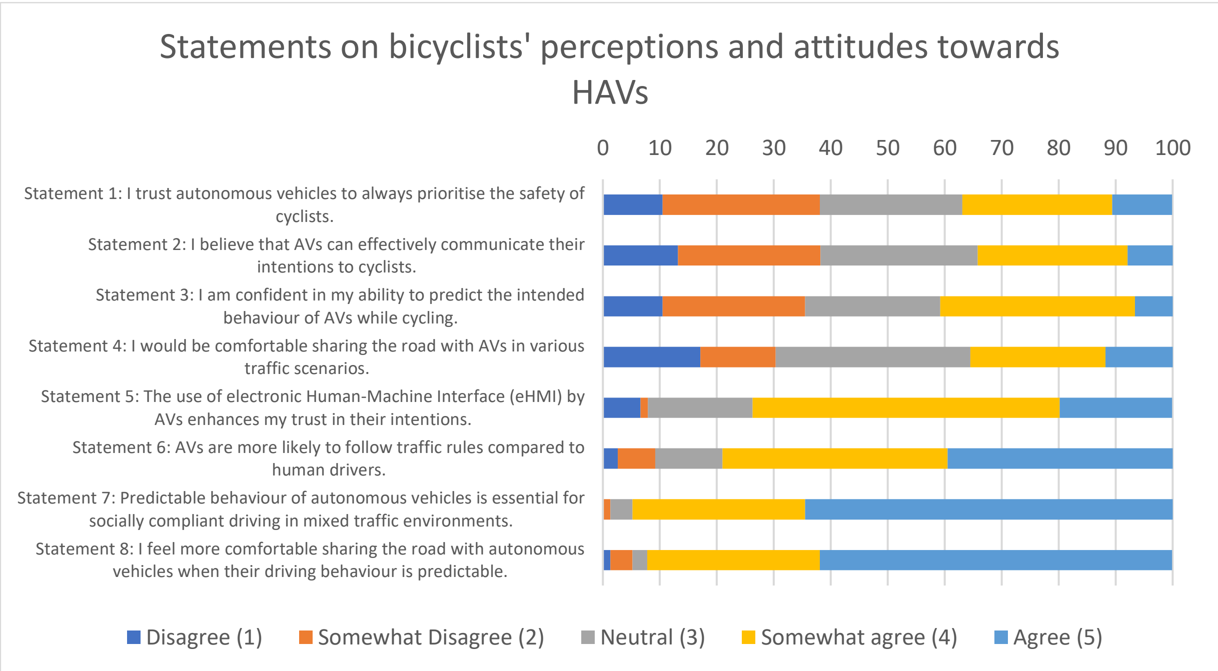


***Figure 12**: Respondents perceptions and attitudes towards HAVs*

Following this, participants were presented with scenario-based questions to gauge their anticipated responses when encountering HAVs at different locations in The Hague. The description for each scenario can be found in Chapter 3.4.

The responses indicated that the clarity of the HAV's intentions plays a significant role in shaping opinions regarding Trust, Perceived Safety and Perceived Social Behaviour. This is particularly evident, as they were set in the same urban environment (i.e., Scenarios 1 and 2).

In Scenario 1, the HAV approached from the left and made its intentions clear to the cyclist by signalling its intention to pass in front. In contrast, Scenario 2, where the HAV did not clearly convey its intentions and passed in front of the cyclist from the left, received the lowest ratings regarding Trust, Perceived Safety and Perceived Social Behaviour levels among all scenarios. This suggests that in challenging traffic scenarios, cyclists need to easily discern the HAV's intentions to feel more confident.

Scenarios 5 and 6 showed similarities to Scenarios 1 and 2, with the HAV approaching perpendicularly from the left while the cyclist intended to proceed straight. However, a significant distinction for Scenarios 5 and 6 was the presence of an external Human-Machine Interface (eHMI) on the HAV, which communicated its intentions to other traffic participants. Descriptive statistics indicate that ratings for Trust, Perceived Safety and Perceived Social Behaviour were higher in these scenarios compared to Scenarios 1 and 2, with Scenario 5 receiving the highest ratings overall. This suggests that a device informing cyclists of HAVs' intentions positively influences perceptions of social HAV driving by bridging the communication gap. This is corroborated by the ratings for Statement 5 (see Figure 6), where 73.6% of respondents expressed positive or very positive views on the use of eHMI to enhance their trust in HAV intentions. Additionally, the prioritisation of cyclists by HAVs in Scenarios 5 and 6 was viewed positively, with Scenario 6 scoring lower than Scenario 5 in Trust, Perceived Safety and Perceived Social Behaviour because of not prioritising cyclists.

Additionally, Scenario 1 (*clear HAV deceleration, clear HAV intention*), Scenario 2 (*smooth HAV deceleration, no clear HAV intention*), Scenario 5 (*use of eHMI, cyclist prioritisation*) and Scenario 6 (*no use of eHMI, no cyclist prioritisation*) supposedly took place in similar settings, however, they showed mixed scores regarding Trust and Perceived Safety, which is in line with people's mixed opinion on their prioritisation by the HAVs (see results of Statement 1 in Figure 6).

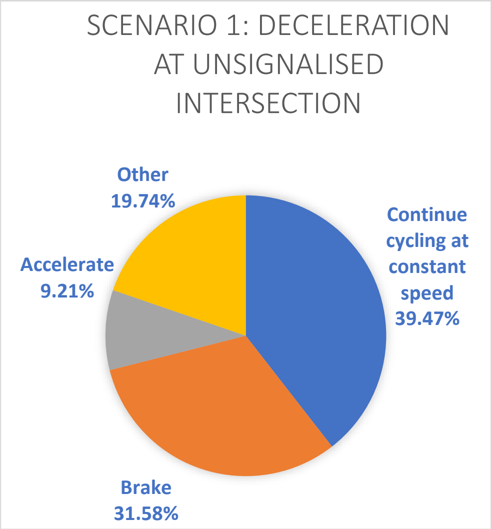
Furthermore, when HAVs move in the same direction as the cyclist at a constant speed (Scenario 3), this seems to exert a positive influence on the cyclist's perceptions of Trust, Perceived Safety and Perceived Social Behaviour. This likely stems from the HAV's predictable behaviour. Conversely, in Scenario 4, despite the HAV moving in the same direction as the cyclist, its sudden acceleration introduces unpredictability into the interaction, negatively affecting perceptions. It is also evident that the HAV's driving dynamics contribute to perceptions of socially compliant driving. In Scenarios 1, 3, 5 and 6, the HAV was either decelerating or braking, which positively influenced participants' views.

Table 4 on the following page summarises the characteristics of each scenario, along with the mean and standard deviation of the responses for Trust, Perceived Safety and Perceived Social Behaviour.

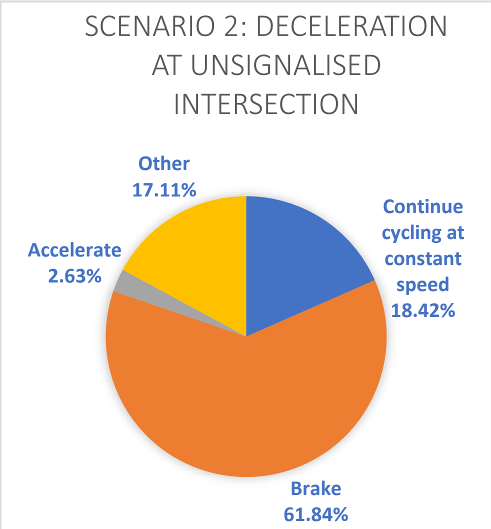
***Table 4**: Descriptive statistics for Trust, Perceived Safety and Perceived Social Behaviour with dark red to dark green highlighting the gradual shift in the agreement levels across the scale from "Disagreement" to "Agreement"*

						Trust		Perceived Safety		Perceived Social Behaviour	
	eHMI	Unsignalised intersection	Direction	Clear Intention	HAV Dynamics	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
Scenario 1	No	Yes	Perpendicular Direction	Yes	Deceleration	3.14	0.976	3.18	1.016	3.59	0.969
Scenario 2	No	Yes	Perpendicular Direction	No	Deceleration	2.36	0.919	2.42	0.853	2.54	0.958
Scenario 3	No	No	Same Direction	No	Constant Speed	3.39	0.981	3.57	0.943	3.51	1.039
Scenario 4	No	No	Same Direction	No	Acceleration	2.76	1.094	2.62	1.032	2.72	1.127
Scenario 5	Yes	Yes	Perpendicular Direction	Yes	Brake	3.66	0.917	3.59	1.11	3.97	1.006
Scenario 6	Yes	Yes	Perpendicular Direction	Yes	Constant Speed	3.03	1.306	2.64	1.186	2.74	1.237
Scenario 7	No	Yes	Perpendicular Direction	Yes	Deceleration	2.89	0.946	2.92	0.949	3.22	0.947

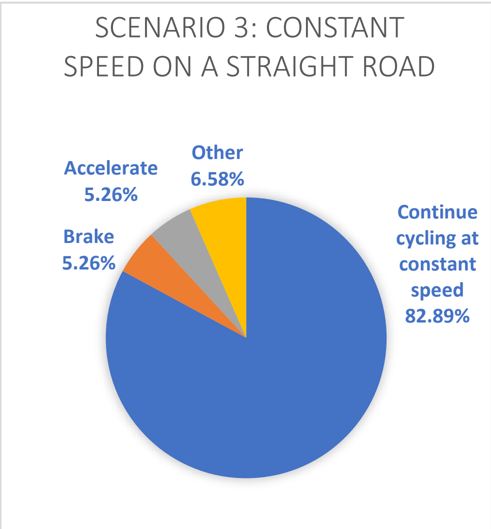
The potential respondents' reactions in each scenario align closely with their responses to questions concerning Trust, Perceived Safety and Perceived Social Behaviour. The following figures provide an insight into how participants would react:



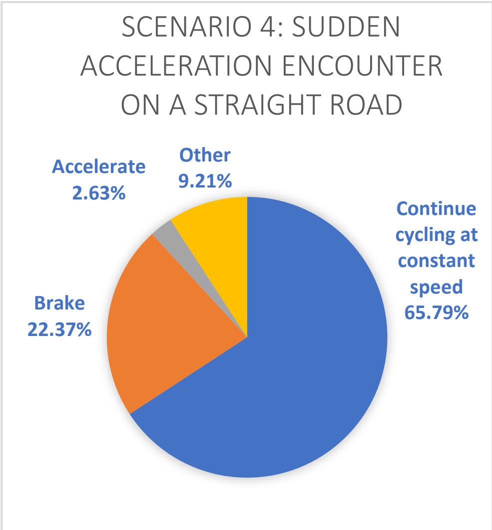
Specifically, responses in Scenario 1 reflect a balanced approach, with nearly 50% of participants choosing to "Continue cycling" or "Accelerate," while the remaining respondents adopt a more cautious approach, either by braking or selecting "Other" as their preferred reaction. Notably, in most cases, the selection of "Other" was predominantly associated with decelerating, a trend observed across the other scenarios as well. It is pertinent to highlight some indicative responses provided by respondents, such as: "*Be very careful and watchful and continue cycle slowly*", "*Slow down to make sure HAV actually decelerate and then continue*" and "*Lower speed*".



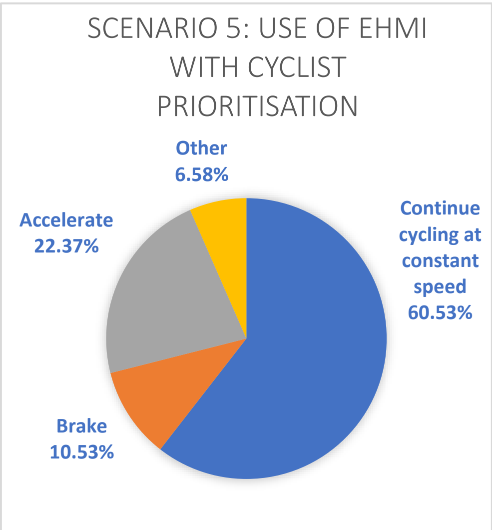
The prevailing reaction of respondents for this instance was to brake. In contrast, a smaller group of respondents showed higher confidence and expressed an intention to continue cycling at constant speed or even accelerating, while the remaining respondents who selected "Other" stated: "*I decrease the speed to make sure that the car stops for me*" and "*Even if the HAV decelerates, there is a lack of trust in if HAV has seen me. I'm not in favour of eHMI, but putting myself in this situation, I think maybe for a while until the public builds trust, eHMI can be helpful*".



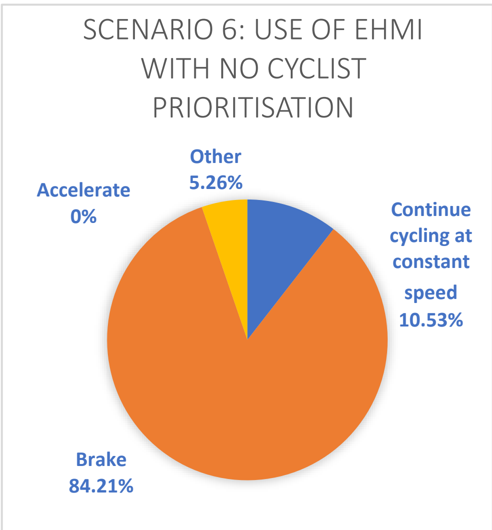
The high ratings of Trust, Perceived Safety and Perceived Social Behaviour had in all likelihood a reflection on the potential behaviour of respondents since the vast majority of them stated that they would continue cycling at a constant speed. This suggests a prevailing tendency among cyclists. Those who replied "Other" expressed various opinions like "*leaning right, maintaining larger space with the main road*" and "*Be very careful and watchful and cycle slowly so that HAV can pass*".



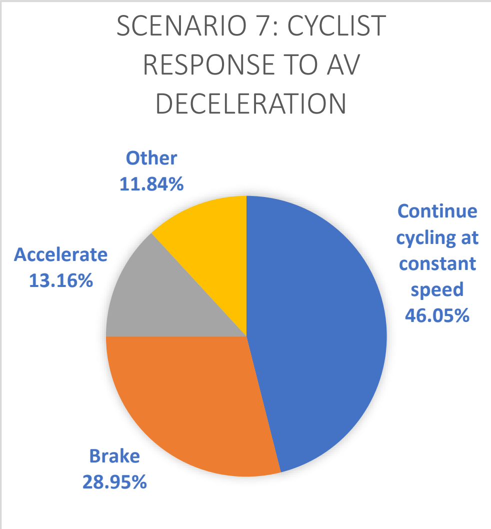
Almost two-thirds of participants indicated they would continue cycling at a constant speed in this scenario. Interestingly, the participants rated with low scores their Trust, Perceived Safety and Perceived Social Behaviour, but they still stated that they would continue cycling. This could be attributed to the fact that driving on a straight road shows fewer challenges than at an unsignalised intersection. A quarter of the respondents opted for more cautious reactions (Brake/Other). At this point, it would be interesting to present some of the responses given by those who opted for “Other”. One participant stated, “*I would brake. But it’s not because it is an HAV. Even if a conventional car passes by abruptly accelerating, I would feel and do the same*”. Another respondent said, “*Stop cycling and avoid the road altogether*”.



This scenario gathered the highest ratings of Trust, Perceived Safety and Perceived Social Behaviour, but it can be observed that the “Continue cycling at constant speed” responses gather less percentage, when compared to Scenarios 3 and 4, where the cyclist is supposed to be moving on a straight road. A remarkable finding is that almost a quarter of participants stated that they would accelerate in this case, indicating a high level of confidence. One out of six respondents showed a cautious attitude. Several notable answers in this instance included responses such as “*Cycle a bit slower. It's fine that it says “has stopped", but if it unexpectedly starts accelerating, I need to be prepared to take evasive action*” and “*Detouring anti-clockwise around the HAV*”.



The low ratings in Trust, Perceived Safety and Perceived Social Behaviour as seen in Table 4 for this scenario were reflected in respondents’ potential reactions. As anticipated, the overwhelming majority indicated their intention to brake, comprising 84% of respondents. Additionally, one out of ten participants expressed their intention to maintain a constant cycling speed, while those who opted for "Other" as their preferred response were very few. Notably, no respondents chose to accelerate. An interesting response from a respondent who selected “Other” was: “*I would decrease my speed to let the HAV go and when it's done executing the turn I would raise my speed again*”.



Last but not least, in this scenario there was a variation to some degree regarding the potential reaction of respondents. Specifically, the most predominant response here was to continue cycling at a constant speed, where almost half of the participants opted for this answer. On the other hand, almost a third stated that they would brake, making this the second most popular answer among participants. A significant portion stated they would accelerate, while many chose "Other". Among those who selected "Other" notable responses included: "*Waiting and/or continue cycling along the sidewalk*" and "*I will slow down as I don't know if the HAV will deviate from its driving path*".

4.3. Statistical analysis of survey findings

The processed information so far has been based on survey data as it was collected in MS Forms. However, there is a need to examine the relationships related to either demographics and /or scenario-related HAV dynamics with Trust, Perceived Safety and Perceived Social Behaviour following the Conceptual Framework of Figure 10.

Therefore, the data need to be analysed and their relationship(s) need to be explored. The data was imported into the IBM SPSS v27 Statistical software for further processing. A preliminary analysis was conducted.

Based on the number of participants belonging to each age group, it is evident that a new age classification is required to have more balanced groups in terms of the number of participants thereby enhancing the statistical significance and representation within the dataset. It can be seen that age groups "45-54", "55-64" and "65 or older" can be merged to provide a more meaningful classification, in terms of the number of participants as illustrated in Table 5. Following this, the new age classification group will be name-coded "45 or older" and will include 13 participants. This is roughly of the same order as the other age groups with the exception of the larger age group of "35-44" which is almost double in size than any of the other age groups.

Regarding the frequency of cycling, it is evident that frequency groups "Once a week" and "Never" were underrepresented with nine (9) and two (2) participants respectively. The proposed new classification "Infrequently", which also includes the "Rarely" group with seventeen (17) participants, yields a more representative frequency group with twenty-eight (28) participants falling in this frequency group.

The "Experience with AVs" classification did not change, its order did. Still, it is important to mention that all three new classifications reflect a more balanced number of participants belonging to each of them and at the same time the classification order regarding the processing in SPSS is in ascending order from the negative to the positive side in terms of order. That is, from younger to older, from less frequent to more frequent and from less experience to more experience. This is required for more effective data processing and analysis.

Table 5 highlights this classification for further processing.

***Table 5**: Renaming of Classification settings for Age Group, Frequency of Cycling and Experience in sharing the roads with AVs*

Age group		Frequency of cycling		Experience with AVs	
Old classification (# respondents)	**New classification (# respondents)**	**Old classification (# respondents)**	**New classification (# respondents)**	**Old classification**	**New classification**
18-24 (14)	18-24 (14)	Daily (28)	Infrequently (28)	Yes	No
25-34 (34)	25-34 (34)	Several times a week (20)	Several times a week (20)	Somewhat	Somewhat
35-44 (15)	35-44 (15)	Once a week (9)	Daily (28)	No	Yes
45-54 (6)	45 or older (13)	Rarely (17)			
55-64 (5)		Never (2)			
65 or older (2)					

To facilitate the statistical analysis, a series of selected tests were performed. Justification for conducting these tests will be given for each test in its corresponding section. The tests in their order of appearance include Bivariate correlation, Repeated Measures One-Way ANOVA and Multinomial Logistic Regression.

4.3.1. Bivariate correlation between variables

Bivariate correlation is used to measure and analyse how strongly two variables relate to each other and the direction of their relationship (negative or positive correlation). Each comparison yields two key results: the correlation coefficient (r) and the significance level (p-value). The correlation coefficient (r), which ranges from -1 to +1, highlights the relationship between the two variables. Negative values correspond to an inverse relationship, a theoretical zero (0) indicates no correlation and +1 denotes an absolute 100% correlation (Larson-Hall, 2010; Pallant, 2016).

The other variable of interest is the significance level (p-value). According to theory, the null hypothesis assumes that the variables in question are not correlated. Hence, they are tested against this hypothesis. It is important to emphasise that the significance level (p-value) does not indicate the strength of the relationship between two variables, which is given by the correlation coefficient (r). Instead, it indicates the level of confidence in the results obtained. Values of $p \leq 0.05$ suggest a low probability that the observed correlation occurred by chance, thereby supporting the hypothesis of statistical significance between the variables (Pallant, 2016).

Correlation analysis requires a number of assumptions to be met. However, for non-parametric data, these assumptions can be relaxed by choosing Spearman's rho (in SPSS bivariate correlation test) as the preferred calculation. This setting is suitable for ordinal data or when non-normality is not met or normality is violated (SPSS analysis, 2024).

In Appendix B: Bivariate correlation, a complete set of correlations is given. Statistically significant correlations are highlighted in yellow. Additionally, other factors related to participants' perceptions and attitudes towards HAVs were again examined concerning Trust, Perceived Safety and Perceived Social Behaviour.

According to Cohen (1988), as a general rule, correlation factors (r) are subjected to the following guidelines:

- Small correlation: r = .10 to .29
- Medium correlation: r = .30 to .49
- Large correlation: r = .50 to 1.00

Concerning large correlations of demographics, no strong correlations seem to exist among them (where r ≥ .50). The same holds for the revised demographics.

In terms of perceptions and attitudes towards HAVs (see Figure 12 in Chapter 4.2.), strong correlations seem to exist between the following pairs in Table 6:

Table 6 *Strong correlations among HAV-related statements*

Variable 1	Variable 2	Correlation factor (r)	Significance (p-value)
Confidence in predicting intended HAV behaviour	Belief in HAVs' Communication	0.537	< .001
Belief in HAV's communicating intentions	Comfortability in Sharing the road with HAVs	0.548	< .001
Comfortability in sharing the road with HAVs	Trust HAVs in prioritising cyclists' safety	0.582	< .001
Comfortability in sharing the road with HAVs	Confidence in cyclist's ability to predict the intended behaviour of the HAV	0.578	< .001
eHMI trust enhancement	Belief in AV's effective communication of intentions	0.532	< .001
eHMI trust enhancement	Comfortability in sharing the road with HAVs	0.544	< .001

Before proceeding, as a reminder, it is noteworthy to remember the scenario descriptions:

Table 7*: Description of Scenarios*

Scenario 1:	Deceleration at unsignalised intersection (clear deceleration, clear indication of intention)
Scenario 2:	Deceleration at unsignalised intersection (smooth deceleration, no clear indication of intention)
Scenario 3:	Constant speed on a straight road
Scenario 4:	Sudden acceleration encounter on a straight road
Scenario 5:	Use of external Human-Machine Interface (eHMI) at intersections (cyclist prioritisation)
Scenario 6:	Use of external Human-Machine Interface (eHMI) at intersections (no cyclist prioritisation)
Scenario 7:	Cyclist response to HAV deceleration

In addition, bivariate analysis of Trust, Perceived Safety and Perceived Social Behaviour reveals that:

- Cyclists who feel comfortable sharing the road with HAVs strongly correlate with higher levels of Trust and Perceived Safety only when HAVs are decelerating or braking in situations where the AV is moving perpendicularly to cyclists.
- Cyclists who view that HAVs equipped with eHMI enhance their trust correlate strongly with higher levels of Trust and Perceived Safety levels in safe situations, such as when the HAV is braking.
- Respondents who believe that AVs' comply with traffic rules correlate with higher Perceived Safety and Perceived Social Behaviour ratings only when the HAV is decelerating or braking.
- Trust, Perceived Safety and Perceived Social Behaviour are generally not significantly correlated with demographic variables such as Gender and Experience with AVs in most scenarios.
- Age Group shows a neutral or no correlation with Trust and Perceived Social Behaviour in most scenarios
- Experience and Familiarity with AVs generally show minimal or no influence on Trust, Perceived Safety and Perceived Social Behaviour in most scenarios.
- The variables Trust, Perceived Safety and Perceived Social Behaviour themselves exhibit strong inter-correlations, indicating they may be capturing overlapping dimensions of respondents' perceptions.

Overall, the data suggests that the clear signalling of intentions from HAVs, especially in perpendicular interactions and at unsignalised intersections, positively impacts cyclists' comfortability and trust enhancement, even in the absence of eHMI. Deceleration and braking dynamics appear to be significant contributors to these perceptions. Respondents seem to be very conservative in generally assigning high levels for Trust, Perceived Safety and Perceived Social Behaviour. They associate these levels strongly with safe situations. On the other hand, through the bivariate correlation analysis, it was found that demographic factors have limited direct influence on Trust, Perceived Safety and Perceived Social Behaviour in most traffic scenarios examined. This indicates that specific situational or contextual factors in each scenario may play a more significant role in shaping these perceptions.

Table 8 on the following page summarises strong correlations between Scenarios and Trust, Perceived Safety and Perceived Social Behaviour (all with p-value < .001, hence statistically significant - see Table 15 in Appendix B).

***Table 8**: Correlations between Scenarios and Trust, Perceived Safety and Perceived Social Behaviour (strong correlations only)*

						Trust			Perceived Safety			Perceived Social Behaviour		
	eHMI	**Unsignalised intersection**	**Direction**	**Clear Intention**	**HAV Dynamics**	**Comfortability in sharing the road with HAVs**	**eHMI trust enhancement**	**Rule compliance of HAVs**	**Comfortability in sharing the road with HAVs**	**eHMI trust enhancement**	**Rule compliance of HAVs**	**Comfortability in sharing the road with HAVs**	**eHMI trust enhancement**	**Rule compliance of HAVs**
Scenario 1	No	Yes	Perpendicular	Yes	Deceleration	0.5	-	-	0.584	0.532	-	-	-	-
Scenario 2	No	Yes	Perpendicular	No	Deceleration	0.536	-	-	0.604	-	-	-	-	-
Scenario 3	No	No	Same	No	Constant Speed	-	-	-	-	-	-	-	-	-
Scenario 4	No	No	Same	No	Acceleration	-	-	-	-	-	-	-	-	-
Scenario 5	Yes	Yes	Perpendicular	Yes	Brake	0.5	0.526	-	-	0.585	0.516	-	0.479	0.488
Scenario 6	Yes	Yes	Perpendicular	Yes	Constant Speed	-	-	-	-	-	-	-	-	-
Scenario 7	No	Yes	Perpendicular	Yes	Deceleration	0.539	-	-	-	-	-	-	-	-

4.3.2. Factors affecting dependent variables - Repeated measures One-Way ANOVA

So far, correlations between Trust, Perceived Safety, Perceived Social Behaviour, demographics and HAV-related responses have been explored. However, it is necessary to further investigate the relationship (if any) between demographics and HAV-related variables and how they influence the measurements of Trust, Perceived Safety and Perceived Social Behaviour across different scenarios.

Trust, Perceived Safety and Perceived Social Behaviour will serve as the dependent variables of interest, while demographics and HAV-related variables will serve as the independent variables. Given that the dependent variables are measured across seven scenarios, the statistical test of Repeated Measures One-Way ANOVA will be employed.

In the Repeated Measures a One-Way ANOVA design, each subject is exposed to multiple conditions or measured on the same continuous scale on several occasions. This design can also compare respondents' answers to different questions or items, provided these questions are measured using the same scale (e.g., 1=strongly disagree to 5=strongly agree).

For this test, it is necessary to have one group of participants measured on the same scale on three or more occasions, under three or more conditions, or on three or more different questions or items (using the same response scale). The test involves one dependent variable (continuous or ordinal, as in a Likert scale) and one (or more) independent variable(s) (categorical).

This statistical test will determine if there are any statistically significant differences between the means among the levels of a within-subjects factor (variables of interest). In this case, these levels are the measurements across all scenarios of the dependent variables: Trust, Perceived Safety and Perceived Social Behaviour.

The null hypothesis for this test is that there are no differences in population means between the time points (scenarios in this case). The test is conducted three times – once for each dependent variable: Trust, Perceived Safety and Perceived Social Behaviour.

Before proceeding with the analysis, it is important to briefly mention which assumptions should be taken into consideration when applying Repeated Measures One-Way ANOVA. As highlighted by Muhammad (2023), these include:

1. The presence of a single dependent variable measured at a continuous level.
2. The inclusion of one within-subject factor containing three or more categorical levels.
3. The absence of significant outliers across any level of the within-subjects factor.
4. The approximate normal distribution of the dependent variable within each level of the within-subjects factor.
5. Equality of variances (i.e., sphericity) among the differences across all combinations of levels within the within-subjects factor.

Regarding assumptions, tests on their validity can be found in Appendix C and D.

At the outset, Repeated Measures One-Way ANOVA was employed for each dependent variable (Trust, Perceived Safety and Perceived Social Behaviour) independently of any demographic variables. This approach investigated how each dependent variable varied across different scenarios. Ordinal Likert scale variables, ranging from "*1: No Trust*" to "*5: Complete Trust*," were transformed.

Theoretically, all variables ranging from demographics and HAV-related Likert scale variables could serve as independent variables. However, after a close examination of the correlations mentioned in Table 8 in Chapter 4.3.1., only the following variables will serve as independent variables:

- eHMI trust enhancement (related to how respondents trust HAVs equipped with eHMI)
- Rule Compliance (as referred to in Statement 6: "*HAVs are more likely to follow traffic rules compared to human drivers.*")
- Comfortability in sharing the roads with HAVs
- Frequency of cycling (revised classification)

These variables, as can be noticed from Table 9 below, exhibit a strong influence (highlighted in yellow) with each of the dependent variables (not in all scenarios, however). These variables will serve as the Between-Subjects factors in the Repeated Measures One-Way ANOVA statistical test since they vary across individuals.

One of the output tables in Repeated Measures One-Way ANOVA is Mauchly's Test of Sphericity. This test examines the null hypothesis that the variances of the differences between the levels of the within-subjects factors are equal. The significance metric (p-value) determines whether the null hypothesis should be rejected. If the p-value is less than 0.05, then the null hypothesis is disproven, leading to the acceptance of the alternative hypothesis (since the variances are not equal, indicating a violation of sphericity.

The table below concisely presents the output for all Repeated Measures One-Way ANOVA for each of the dependent variables: Trust, Perceived Safety and Perceived Social Behaviour.

The Within-Subjects section in Table 9 depicts the interaction of independent variables eHMI trust enhancement, Frequency of cycling and Comfortability in sharing the roads with HAVs with the dependent variables Trust, Perceived Safety and Perceived Social Behaviour.

The Between-Subjects section depicts how the independent variables affect the dependent variables Trust, Perceived Safety and Perceived Social Behaviour since they vary across individuals.

***Table 9**: Cumulative Repeated Measures One-Way ANOVA for dependent variables*

	Variable	Trust	Perceived Safety	Perceived Social Behaviour
		Significance (p-value)		
Mauchly's Test of Sphericity		< .001	< .001	.013
Within-Subjects	Scenario (Greenhouse Geisser)	0.168	0.173	0.864
	eHMI	0.074	0.748	0.590
	Rule_Compliance	0.081	0.117	0.165
	Comfortability	0.001	0.201	0.889
	Frequency_Rev	0.131	0.386	0.296
Between-Subjects	eHMI	0.006	< .001	0.008
	Rule_Compliance	0.099	0.016	0.027
	Comfortability	0.002	< .001	0.008
	Frequency_Rev	0.015	0.010	0.062

Significant relationships are highlighted in yellow. Here are the key findings:

The sphericity assumption, in Repeated Measures One-Way ANOVA, refers to the condition where the variances of the differences between all possible pairs of within-subject conditions (levels) are equal. For the assumption to be met the p-value must be > .05.

In this series of tests, Mauchly's test of sphericity revealed that the sphericity assumption has been violated since the corresponding p-value < .05. Significance values, in Table 9, refer to the Greenhouse-Geisser correction (since sphericity has been violated) revealing that the scenarios per se do not affect Trust, Perceived Safety and Perceived Social Behaviour.

It is rather the combination of the Between-Subjects factors that play a crucial role in affecting Trust, Perceived Safety and Perceived Social Behaviour. As can be seen from the table above, eHMI, Rule Compliance, Comfortability in sharing the roads with HAVs and the Frequency of cycling determine the assessment of Trust, Perceived Safety and Perceived Social Behaviour. Their influence is highlighted in yellow in the table above.

The introduction of Rule Compliance is very influential. Had this factor been absent, the situation would be completely different for the significance p-values of Trust, Perceived Safety and Perceived Social Behaviour.

The influence is illustrated in Table 10 below. With Rule Compliance absent, the scenario influences Trust, Perceived Safety and Perceived Social Behaviour since the significance p-values are completely different, well below < .05

***Table 10**: Cumulative Repeated Measures One-Way ANOVA for dependent variables without Rule_Compliance factor*

	Variable	Trust	Perceived Safety	Perceived Social Behaviour
		Significance (p-value)		
Mauchly's Test of Sphericity		< .001	< .001	0.004
Within-Subjects	Scenario (Greenhouse Geisser)	0.035	0.013	0.023
	eHMI	0.154	0.737	0.738
	Frequency_Rev	0.219	0.636	0.38
	Comfortability	0.006	0.24	0.861
Between-Subjects	eHMI	0.013	0.003	0.073
	Frequency_Rev	0.011	0.010	0.064
	Comfortability	< .0001	< .0001	0.004

With Rule Compliance included in the factors to be examined (as of Table 9), here are the main findings:

- From Within-Subjects
    - Scenarios do not play a significant role in assessing the outcome of the dependent variables
    - Comfortability in sharing the roads with HAVs interacts with Trust only
- From Between-Subjects
    - eHMI trust enhancement (related to how respondents trust HAVs equipped with eHMI) affects Trust and Perceived Safety
    - Rule Compliance does affect Perceived Safety and Perceives Social Behaviour
    - Comfortability in sharing the roads with HAVs affects all dependent variables significantly
    - Frequency of cycling affects Trust and Perceived Safety

Complete statistical tests can be found in Appendix D: Trust, Appendix D: Perceived Safety, and Appendix D: Perceived Social Behaviour.

The findings from the Repeated measures One-Way ANOVA reveal that HAVs equipped with eHMI systems, the belief that self-driving vehicles are more likely to be rule compliant, people's comfortability with sharing the roads with HAVs and the frequency of cycling significantly contribute to measurements for Trust, Perceived Safety and Perceived Social Behaviour.

4.3.3. Multinomial logistic regression for cyclists' intended reaction per scenario

From the conceptual framework (see Chapter 4.1.), cyclists' intended behaviour with AVs is linked to Trust, Perceived Safety and Perceived Social Behaviour. Other factors may also influence intended behaviour, including demographic factors and HAV dynamics, as well as respondents' views related to HAVs, such as their familiarity with AVs at any level of automation and their experience with AVs as a passenger and/or driver, among others.

Statistics provides a method to study and analyse the influence of a series of variables, referred to as independent variables and model their effect on a decision variable, which has levels (categories) in its characteristics. This variable will serve as the dependent categorical variable. Multinomial Logistic Regression (MNLR) is one such method to employ.

The primary aim is to discern how a set of predictor variables impacts the likelihood of a case being classified into each category. This method offers valuable insights into the connections between independent variables and a categorical outcome, thus allowing us to make informed decisions grounded in the probabilities of group membership.

Theoretically, all variables could serve as independent variables. However, preliminary tests showed that the following variables could result in acceptable models. These are Age Group, Familiarity with AVs, Experience and scenario-related Trust, Perceived Safety and Perceived Social Behaviour. The dependent variable will be the reaction of the cyclist for each scenario under examination.

Therefore, seven independent Multinomial Logistic Regression tests were performed to assess how well the model fits, one per scenario. The test results can be found in Appendix E.

MNLR requires some assumptions to be satisfied. Among them, contributing independent variables should not be perfectly collinear. The correlation levels for Trust vs Perceived Safety range between .600 and .804, Trust vs Perceived Social Behaviour range between .506 and .741 and Perceived Safety vs Perceived Social Behaviour range between .287 and .792.

Cyclists' intended reaction will serve as the dependent variable and the revised Age Group (nominal variable), revised Experience (nominal variable), Familiarity with AVs (nominal variable) and scenario-related Trust (ordinal variable), Perceived Safety (ordinal variable) and Perceived Social Behaviour (ordinal variable) will serve as the independent variables.

According to Laerd (2024), MNLR requires the following assumptions:

- Nominal Dependent Variable is measured at the nominal level with at least 3 groups
- One or more independent variables are either continuous, nominal or ordinal
- Independence of Observations. These should be independent of each other
- No Perfect Multicollinearity among independent variables
- Adequate Sample Size
- Absence of Outliers

In hypothesis testing, the null hypothesis (H_0) is examined to ascertain there is no significant relationship between the independent variables and the outcome categories. The alternative hypothesis (H_1) asserts that at least one independent variable significantly influences the likelihood of belonging to specific categories (SPSS analysis, 2024).

In this context, the significance of the coefficients associated with each independent variable for each category is examined. If any coefficient has a p-value less than the selected significance level (.05 in this case), it indicates that the corresponding variable significantly influences the probability of belonging to that category.

Regarding the Reaction classification response, after consideration of the original responses of the survey participants, the need for a smoother classification distribution was apparent. Hence, in Table 11, the following response classification was adopted.

***Table 11**: Revised Reaction Classification Categories*

Reaction of cyclists	
Old classification	**New classification**
Continue cycling at a constant speed	Brake
Brake	Decelerate
Accelerate	Continue cycling at a constant speed
Other	

Seven MNLR tests were run, one for each scenario. The goal is to assess whether the cyclists' intended reaction can be modelled.

Before proceeding with the findings, a clarification of the results is needed. MNLR produces a series of results in tabular form. The most important tables refer to the Goodness of Fit, Model Fitting Information, Likelihood ratio Tests and Parameter Estimates (mainly for continuous variables).

- Goodness of Fit table assesses the overall fit of the model by comparing the observed frequencies with the expected frequencies under the Null hypothesis (where the model fits perfectly). P-values range from 0 to 1, with 0 meaning unacceptable fit and 1 meaning excellent fit. Therefore, the higher the p-values, the better the fit.

The table produces two statistic metrics, Pearson and Deviance. They do not usually agree.

- The Pearson statistic assesses the overall Goodness of Fit of the model by comparing the observed frequencies with the expected frequencies under the null hypothesis (where the model fits perfectly). It adheres to a chi-square distribution with degrees of freedom calculated as the number of categories minus the number of estimated parameters. A small Pearson p-value (typically ≤ 0.05) suggests that the model does not adequately fit the data. In other words, the observed and expected frequencies significantly differ. Pearson is used when the simultaneous evaluation of the overall fit of the model across all categories is desired.
- The Deviance statistic also assesses the goodness of fit by comparing the observed and expected frequencies. The Deviance statistic will be considered in this series of tests.

The next significant output table, Model Fitting Information returns a significance metric p-value. A p-value < .05 reinforces that the variables statistically significantly improve the model.

Likelihood Ratio tests reveal if any statistical significance exists for the independent variables under examination. If so, these variables are statistically significant predictors of cyclist behaviour. Again, p-values < .05 are considered statistically significant. Conversely, p-values > .05 are considered insignificant, meaning they do not play a crucial role in the modelling of the cyclists' reaction to the scenario situation.

Table 12 summarises the results of these tests.

***Table 12**: MNLR Cumulative Results for all Scenarios highlighting the strong influence of Independent Variables in modelling cyclist's reaction*

		Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
		Significance (p-value)						
Likelihood ratio tests	Trust	.033	< .001	1.000	.367	.075	.083	.524
	Perceived Safety	.021	< .001	.964	.046	.960	.010	.065
	Perceived Social Behaviour	.538	< .001	.998	.078	< .001	.698	.998
	Familiarity with AVs	.549	< .001	.900	.347	.149	.010	.415
	Age group	.006	< .001	.284	.169	< .001	< .001	.875
	Experience either as a passenger or a driver with AVs	.207	< .001	.587	0.383	< .001	< .001	.682
	Goodness of Fit	1.000	1.000	1.000	1.000	1.000	1.000	.997
	Model fitting sig.	< .001	< .001	.023	< 0.001	.001	.026	.034
Classification (% accuracy)	Brake	85.2	98	100	78.9	100	100	78.3
	Deceleration	40	100	100	100	100	100	42.9
	Continue cycling	87.2	88.2	100	94.4	98.5	100	87
	Overall	**80.3**	**96.1**	**100**	**90.8**	**98.7**	**100**	**80.3**

Cyclists' reactions to HAVs in various traffic settings were explored in relation to the impact of specific factors, such as Trust, Perceived Safety, Perceived Social Behaviour, respondent's familiarity with AVs, age group and the experience someone has either as a passenger or a driver with AVs. From the previous table, the following inferences can be drawn:

- The employment of MNLR managed to predict people's potential reaction to a large extent, with the percentages ranging from 80.3% (Scenario 1 - *clear HAV intention, clear HAV deceleration*- and Scenario 7 -*HAV approach from the opposite direction executing a left turn*-) to 100% (Scenario 3 -*constant HAV speed on a straight road*- and Scenario 6 - *use of eHMI, no cyclist prioritisation* -).
- Age group appears to be a significant predictor in four out of seven scenarios, specifically in Scenario 1 (*clear HAV intention, clear HAV deceleration*), Scenario 2 (*not clear HAV intention, smooth HAV deceleration*), Scenario 5 (*use of eHMI, cyclist's prioritisation*) and Scenario 6 (*use of eHMI, no cyclist prioritisation*).
- Experience with AVs either as a driver or a passenger is a significant predictor for Scenario 2 (*not clear HAV intention, smooth HAV deceleration*), Scenario 5 (*use of eHMI, cyclist's prioritisation*) and Scenario 6 (*use of eHMI, no cyclist prioritisation*).
- Perceived Safety is a significant factor for Scenario 1 (*clear HAV intention, clear HAV deceleration*), Scenario 2 (*not clear HAV intention, smooth HAV deceleration*), Scenario 4 (*sudden HAV acceleration on a straight road*) and Scenario 6 (us*e of eHMI, no cyclist prioritisation*).
- The cases where the cyclists opted for decelerating showed the lowest accuracy percentages.
- Scenario 2 (*clear HAV intention, smooth HAV deceleration*) consistently shows very high significance across all independent variables and very high classification accuracy (96.1%).

These findings indicate that age, experience with AVs, familiarity with the concept of socially compliant driving, trust, perceived safety and perceived social compliance significantly influence cyclists' reactions.

5. Discussion, limitations and recommendations

5.1. Discussion

The survey originated from a conceptual framework that was developed based on findings found in the literature review and subsequently incorporated inputs from various experts. According to Nordhoff et al. (2020), individuals often experience reduced feelings of safety in a shared space environment. Consequently, the scenarios were designed to have participants envision themselves cycling at unsignalised intersections and the majority of the scenarios examined cases where cyclists encounter HAVs perpendicularly.

Through the survey analysis, several interesting findings were drawn. Precisely, respondents tend to show mixed trust when it comes to their prioritisation by the HAVs. For that reason, the clarity with which the HAV communicates its intentions exerts a direct influence on cyclists' Trust, Perceived Safety and Perceived Social Behaviour, especially in challenging traffic scenarios, where the likelihood of giving priority to a cyclist is possible (e.g., at an unsignalised intersection). Two striking examples which validate this conclusion are Scenario 1 (*clear HAV deceleration, clear HAV intention*) and Scenario 5 (*use of eHMI, cyclist prioritisation*) which scored significantly higher compared to their counterparts (Scenario 2 -*smooth HAV deceleration*- and Scenario 6 -*use of eHMI, no cyclist prioritisation*-).

In the same fashion, the clarity of intention can be facilitated by using eHMI. Again Scenarios 1, 2 and 5, 6, which are comparable since they take place at an unsignalised intersection where the HAV approaches from the left intending to move in front of the cyclist, show that the ratings for Scenarios 5 & 6, which both used eHMI, were higher when compared to Scenarios 1 & 2. It is worth noting that the 5th Statement regarding bicyclists' perceptions and attitudes towards HAVs ("*The use of electronic Human-Machine Interface (eHMI) by HAVs enhances my trust in their intentions*") received high ratings, implying that such a device is considered important by many.

This aligns with findings by Berge et al. (2023), Nordhoff et al. (2020) and Berge et al. (2022), which argue that the lack of explicit human-to-human communication could be mitigated by eHMIs, at least in the initial stages of HAV deployment. However, a counter-argument is that cyclists, moving at higher speeds than pedestrians, may find it more challenging to read a message from an HAV. In this instance, an on-bicycle HMI might be proven to be more effective in HAV-cyclist interactions.

Further, the prioritisation of cyclists is an element which was highly appreciated in Scenario 5 (*use of eHMI, cyclist prioritisation*) by the respondents, as it gathered the highest ratings among all Scenarios. Notably, the mean score of Perceived Social Behaviour of HAV was 3.97, suggesting a much-favoured HAV behaviour.

Another finding is that the predictability of HAV's behaviour is favoured by respondents, since Scenario 3 (*constant speed of HAV on a straight road*) and Scenario 5 (*use of eHMI, cyclist prioritisation*), where the HAV had a clearly predictable driving behaviour without any fluctuation in its behaviour, gathered the highest mean scores for Trust, Perceived Safety and Perceived Social Behaviour. On the other hand, in ambiguous situations where the HAV shows unclear intentions (e.g., Scenario 2) or unpredictable behaviour (e.g., Scenario 4) the mean scores were among the lowest. The latter is also in line with the 7th Statement ("*Predictable behaviour of autonomous vehicles is essential for socially compliant driving in mixed traffic environments*") and the 8th Statement ("*I feel more comfortable sharing the road with* *autonomous vehicles when their driving behaviour is predictable*”), which both received overwhelming support by respondents.

Last but not least, the HAV driving dynamics seem to matter as well and this can be seen in Scenario 1 (*clear HAV deceleration, clear HAV intention*), Scenario 5 (u*se of eHMI, cyclist prioritisation*) and Scenario 7 (*HAV deceleration while approaching from the opposite direction*) where the mean scores for Perceived Social Behaviour were among the highest.

It is also important to highlight participants’ feedback. Specifically, they expressed scepticism regarding the potential replacement of human drivers by HAVs. Some indicative responses included: “*Human nature cannot be replaced in decision-making*”, ”*Even when you trust the vehicle, it will take time to comprehend the fact that no human is behind the wheel*”, “*I consider HAVs unpredictable because you rely on sensors alone*” and “*The problem is that in practice you cannot recognise an HAV as such*”. Further, regarding their expectations of HAV reliability and behaviour, some respondents stated: “*In general, I expect the HAV to be more reliable than human drivers*”, "*HAVs should imitate human drivers to be acceptable for other road users*" and “*HAVs should indicate their intentions on the road*”. Lastly, concerning their safety and interaction with other road users, some respondents asserted: “*I prefer cycle lanes to be separate from cars to minimise interaction*” and “*I hope HAVs will be tested in various scenarios to eliminate risks for cyclists*”.

5.2. Limitations

As it has already been mentioned, four expert participants were interviewed. The first two experts were mechanical engineers and had similar views regarding the conceptual determinants of socially compliant driving behaviour, focusing more on the technical aspects of Highly Automated Vehicles (HAVs). The third expert (safety and security scientist) introduced an enhancement by suggesting a division between cyclist-related elements and HAV-related elements. Additionally, the fourth expert (road safety scientist) agreed with the revised conceptual framework and provided minor comments, indicating that further expert input could refine the framework even more effectively. Therefore, seeking advice from additional experts might provide a more comprehensive perspective, potentially strengthening the conceptual framework.

Another limitation arises from the absence of HAVs in real-world driving situations. Consequently, respondents have formulated opinions based on past experiments or personal speculations about HAV driving behaviour, resulting in responses that may not fully reflect real-world scenarios. Future surveys could introduce more realistic conditions (e.g., via VR or real-life experiments) to help respondents better understand cyclist-HAV interactions. Some participants may have responded hastily or not fully imagined the scenarios. Online questionnaires often prompt quick answers, potentially overlooking details. Additionally, respondents might have felt pressured to conform to popular opinions, skewing their responses. Cyclists may behave differently in real-traffic conditions compared to their survey answers.

Besides, another limitation arises from the participants' residence in the Netherlands, known for its prominent cycling culture. This cultural context may influence participants' perceptions and behaviours regarding HAVs and cycling interactions, potentially limiting the generalisability of statistical findings in other countries with different cycling norms and infrastructure. Hence, research in different cultural contexts would help generalise the findings and adapt them to diverse traffic environments.

Furthermore, although the sample size of 76 participants was neither small nor large, it may not have been adequately representative. In addition, of the 76 participants, a fraction came from Delft University of Technology, where people are more likely than average to be highly familiar with new technologies and to take a more sceptical view of them. For instance, merely 22 out of the total 76 respondents indicated unfamiliarity with the notion of socially compliant driving. Moreover, the predominance of participants from Delft University of Technology influenced the demographic composition of the study, with a significant proportion being young (approximately 63% were under 34 years old), while middle-aged and elderly participants were notably underrepresented. Additionally, the sample exhibited a disproportionate number of males (58%) with a substantial academic background. Consequently, future research should aim for greater gender balance and demographic diversity. Additionally, it would be valuable to explore how different factors, such as weather or lighting conditions, affect cyclists.

Moreover, in the design of the online survey, it was observed that respondents frequently selected “Other” in scenario-related questions, indicating that their potential reaction would differ from “Brake”, “Accelerate” or “Continue cycling at a constant speed”. Most of the time, their responses suggested, either directly or indirectly, that they would opt for decelerating. This issue was addressed in the design of the SPSS file by processing their response to the respective categorical reaction. However, had this option been explicitly provided, the results might have differed.

5.3. Recommendations

Given the positive reception of eHMI (electronic Human-Machine Interface) by cyclists, further research should focus on developing and optimising such devices. Studies should explore various designs, communication modalities (e.g., visual, auditory) and their effectiveness in enhancing Trust, Perceived Safety and Perceived Social Behaviour in different traffic scenarios.

Additionally, conducting long-term studies to track changes in cyclists' perceptions and behaviours as HAV technology evolves is crucial. These studies can identify trends, adaptation processes and long-term effects of HAVs on cyclist behaviour and safety. Furthermore, future research should adopt interdisciplinary approaches, integrating insights from human factors, urban planning, psychology and computer science. This holistic approach can enhance understanding of cyclist-HAV interactions and inform the development of more effective and user-friendly HAV systems.

Exploring the impact of various policy and regulatory frameworks on cyclist-HAV interactions is also essential. Research should assess how laws and guidelines can be tailored to safely integrate HAVs into mixed traffic environments with a specific focus on vulnerable road users such as cyclists.

Lastly, future studies could investigate how environmental factors, such as weather conditions (rain, snow, fog) and different lighting conditions (daylight, dusk, night-time), influence cyclist-HAV interactions. These factors significantly affect visibility and road conditions, thus impacting overall safety.

6. Conclusion

The research seeks to explore cyclists' perceptions of what they consider the social driving behaviour of highly automated vehicles. Initially, a conceptual framework was developed through a literature review and expert interviews to identify the key determinants of socially compliant driving behaviour. This framework formed the basis for a questionnaire designed to capture cyclists' expectations about the social behaviour of HAVs. To facilitate participants' understanding, traffic scenarios were presented using visual aids, including images depicting the scenarios and their locations, accompanied by graphical representations.

6.1. Addressing the research questions

Sub-question 1: What are the conceptual determinants of socially compliant driving behaviour?

Through the conceptual model, which was based on the literature review and expert suggestions, it was deemed possible to define the conceptual determinants that shape the socially compliant behaviour of highly automated vehicles from cyclists' perspective.

The interaction between cyclists and HAVs involves two distinct agents. Although HAVs are essentially machines and cannot directly negotiate or adjust their driving behaviour, this limitation is partially mitigated by the use of electronics and sensors, which bridge this gap. Therefore, a feedback loop between cyclists and HAVs can indeed be considered. The primary HAV elements involved during an interaction are the driving style of the HAV, which influences the dynamics of HAV driving and the way the self-driving vehicle communicates its intentions.

On the cyclists' side, the relevant factors include demographic characteristics, cycling frequency, familiarity with AVs and the type of infrastructure (e.g., dedicated bicycle lanes or shared bicycle lanes). These elements influence cyclists' trust, perceived safety and perceptions of the social behaviour of HAVs. Each of these three factors is interrelated and their combination affects the intended behaviour of the cyclist.

Sub-question 2: Under which conditions do cyclists perceive a HAV to drive in a social manner?

The survey analysis showed that various aspects of HAV driving seem to matter for cyclists. More specifically, respondents tend to show mixed trust when it comes to their prioritisation by the HAVs. For that reason, the clarity with which the HAV communicates its intentions exerts a direct influence on cyclists' Trust, Perceived Safety and Perceived Social Behaviour, especially in challenging traffic scenarios, where the likelihood of giving priority to a cyclist is possible.

Moreover, the predictability of HAV behaviour, along with the clarity of HAV intentions is favoured by respondents and this was reflected in Statement 7 ("*Predictable behaviour of autonomous vehicles is essential for socially compliant driving in mixed traffic environments*") and in Statement 8 ("*I feel more comfortable sharing the road with autonomous vehicles when their driving behaviour is predictable*") regarding cyclists' perceptions and attitudes towards HAVs and also by the scores given in the Scenarios. Predictable HAV behaviour with clear driving intentions can be achieved using eHMI, which was widely supported by respondents in Statement 5: "*The use of electronic Human-Machine Interface (eHMI) by HAVs enhances* *my trust in their intentions*". Finally, the HAV driving dynamics seem to matter as well. Cyclists prefer HAVs to yield priority to them at intersections or maintain a constant speed when moving alongside them, eliminating any unpleasant surprises.

Sub-question 3: Which factors influence cyclists' perceptions and expectations of HAVs regarding Trust, Perceived Safety and Perceived Social Behaviour?

The current research proved, through bivariate analysis, that Trust, Perceived Safety and Perceived Social Behaviour are highly correlated with cyclists' comfortability in sharing the road with HAVs (Statement 4), the use of eHMIs and rule compliance of HAVs'. It is worth mentioning, that demographic factors did not appear to significantly correlate with respondents' perceptions and expectations regarding their interaction with HAVs.

From the Repeated Measures One-Way ANOVA, it can be inferred that HAVs equipped with eHMI strongly affect Trust, Perceived Safety and Perceived Social Behaviour. This is not a surprise. The same holds for comfortability in sharing the roads with HAVs. The frequency of cycling also strongly affects Trust and Perceived Safety ratings and to a lesser extent, it affects Perceived Social Behaviour. It could also be notably mentioned that the belief that HAVs are more likely to be rule-compliant strongly affects Perceived Safety and Perceived Social Behaviour much more than the different scenarios do.

Sub-question 4: Do Trust, Perceived Safety and Perceived Social Behaviour affect the cyclists' intended behaviour? If so, what other factors might also influence this intended behaviour?

It has been proven through Multinomial Logistic Regression that cyclists' intended behaviour is indeed influenced by Trust, Perceived Safety and Perceived Social Behaviour.

Through preliminary tests, it was found that also the Age Group, Familiarity with the concept of socially compliant driving and the Experience someone has either as a passenger or driver with HAVs could contribute to the model as well. Hence, seven tests were run, where it was proved that the MNRL method could predict to a large extent cyclists' potential reaction to the situation.

Main research question: What factors do cyclists consider important for the social driving behaviour of HAVs?

The analysis revealed that cyclists tend to feel uneasy in situations perceived as uncertain or unpredictable. This tendency is clearly illustrated by the ratings for each scenario. Table 4 in Chapter 4.2 substantiates this as scenarios with clear intentions received high scores in terms of Trust, Perceived Safety and Perceived Social Behaviour. To address the issue of clarity in HAV's intentions, using eHMI has proven to be an effective solution. Specifically, this was supported several times in the survey by respondents, as Statement 5 (see Figure 12 in Chapter 4.2.) predominantly received positive ratings and Scenario 5, which included the use of eHMI by an HAV, scored the highest ratings in Trust, Perceived Safety and Perceived Social Behaviour.

Moreover, participants' comfort levels with sharing roads with HAVs and their frequency of cycling were also found to positively influence Trust, Perceived Safety and Perceived Social Behaviour. Furthermore, the compliance of HAVs with traffic laws markedly increases Perceived Safety and Perceived Social Behaviour, having a more substantial effect than the different scenarios evaluated. It is also interesting to observe that demographic factors did not prominently shape participants' perceptions of their interactions with HAVs in this study.

6.2. Scientific implications

The primary contribution of this thesis is the introduction of cyclists' perspectives on the socially compliant behaviour of HAVs into the academic literature. Specifically, this research developed a conceptual framework to describe the key elements involved in the cyclist-HAV interaction. Notably, no similar framework was found in the existing literature, even for the interaction between cyclists and conventional vehicles. Thus, this research provides a valuable framework that future researchers can use to explore the interaction between cyclists and HAVs more deeply.

Furthermore, although eHMIs are currently designed to enhance pedestrian-HAV interactions, this research found that cyclists also respond very positively to the employment of such devices as it has significantly boosted cyclists' Trust, Perceived Safety and their perception of socially compliant behaviour from HAVs. This finding suggests that future researchers should focus on developing similar devices for cyclists, which could, in turn, put pressure on car manufacturers to adopt these innovations.

6.3. Societal applications and implications

The findings of this thesis provide important insights into the numerous aspects influencing cyclists' views of the social driving of HAVs, which may be used in policy-making and practice such as in urban planning and infrastructure design, the findings of this study provide an interesting narrative for urban planners and policymakers. Thus, authorities can tailor infrastructure developments to better meet the needs of cyclists by understanding their expectations and preferences regarding the implementation of HAVs in urban areas. Specifically, dedicated cycling lanes, safe intersections and cyclist-friendly road designs can be promoted, fostering a safer coexistence between cyclists and HAVs. Also, by aligning infrastructure planning with cyclists' preferences and expectations, cities can take decisive steps in moving towards sustainable and inclusive mobility solutions that support active transportation and enhance road safety.

Moreover, the findings of this research may benefit manufacturers in providing a deeper understanding of cyclists' perceptions. By incorporating features and behaviours that resonate with cyclists' expectations, such as clear communication methods, AV manufacturers can enhance the trust and acceptance of HAV technology among cyclists. The eHMIs emerge as a pivotal tool for bridging the communication gap between cyclists and HAVs, providing real-time feedback and signalling intentions to foster smoother interactions. The synthesis of research insights and technological innovation is critical to achieving HAVs' full potential as safe and reliable traffic agents in urban mobility. In addition, regulatory frameworks and standards can be informed by the findings of this research, ensuring that HAVs comply with societal norms and expectations regarding social driving behaviour. Policymakers can develop regulations and guidelines for HAV communication with cyclists and establish safety requirements for HAV-cyclist interactions. Public awareness and education campaigns can also be devised to inform cyclists and other road users about HAV technology, safety protocols and best practices for interacting with autonomous vehicles.

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Appendices

A. Online Survey

Survey on Social Driving Style of Highly Automated Vehicles (HAVs) from cyclists' perspective

Dear participant,

You are being invited to participate in a research study titled “A social driving style of highly automated vehicles from cyclists’ perspective”. This study is being done by Alexandros Dimitroulis from Delft University of Technology.

The purpose of this research study is to explore the interactions between cyclists and Highly Automated Vehicles (HAVs) (i.e., level of automation 4 and 5*) at unsignalised intersections with a focus on non-dedicated bicycle lanes and shared roadways, aiming to understand which driving behaviours of automated vehicles are considered social. It will take you approximately 10 minutes to complete this survey.

Your responses will be kept confidential throughout this survey process, ensuring anonymity. Only aggregated data will be used for the Master thesis dissertation at Delft University of Technology. Your involvement in this study is entirely optional. You are free to quit the survey at any moment without any consequences.

If any question arises, please contact Alexandros Dimitroulis.

** For more information on the levels of automation, you may check the following link: https://www.synopsys.com/automotive/autonomous-driving-levels.html#6*

** By clicking here you agree to this opening statement.*

◯ *I have understood the information presented above and agree to participate in this study.*

Demographics

What is your gender?

◯ Male

◯ Female

◯ Prefer not to say

In which age group do you belong?

◯ 18 - 24

◯ 25 - 34

◯ 35 - 44

◯ 45 - 54

◯ 55 - 64

◯ 65 or older

How often do you ride a bicycle?

◯ Daily

◯ Several times a week

◯ Once a week

◯ Rarely

◯ Never

Do you have experience as a driver/passenger with Automated Vehicles (AVs) of any level (e.g., adaptive cruise control, autopilot, etc.)?

◯ Yes

◯ Somewhat

◯ No

What is the highest level of education you have completed?

◯ High-school diploma

◯ Technical/vocational training

◯ Bachelor's degree

◯ Master's degree

◯ Doctoral degree

◯ Other

Your perspectives on Socially Compliant AV Driving

How familiar are you with the concept of socially compliant driving when it comes to Automated Vehicles (AVs)?

◯ Not familiar

◯ Somewhat familiar

◯ Moderately familiar

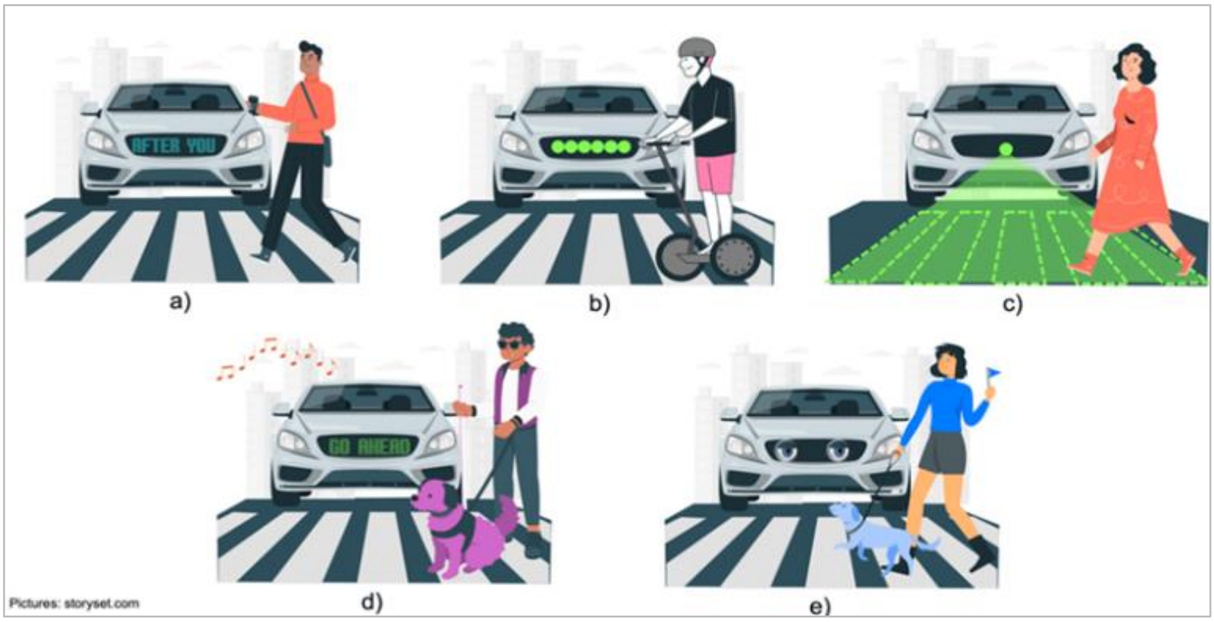
◯ Quite familiar

◯ Very familiar

In your opinion, what specific behaviours or actions by AVs contribute to socially compliant driving?

Some useful brief definitions before proceeding to the next sections.

- **Socially compliant driving**: behaving predictably in interactions with both human and autonomous agents, especially in various social dilemmas.
- **External Human-Machine Interface (eHMI)**: communication tools positioned outside of a vehicle, enabling interaction with nearby road users. An example is an electronic display on the front of the car. (*See image below*)



Statements on cyclists' perceptions and attitudes towards HAVs

On a scale from 1 to 5, please indicate the extent to which you agree or disagree with the following statements regarding HAVs and cyclists.

Statement 1: "I trust autonomous vehicles to always prioritise the safety of cyclists."

Strongly disagree 1 ◯◯◯◯◯ 5 *Strongly agree*

Statement 2: "I believe that HAVs can effectively communicate their intentions to cyclists."

Strongly disagree 1 ◯◯◯◯◯ 5 *Strongly agree*

Statement 3: "I am confident in my ability to predict the intended behaviour of HAVs while cycling."

Strongly disagree 1 ◯◯◯◯◯ 5 *Strongly agree*

Statement 4: "I would be comfortable sharing the road with HAVs in various traffic scenarios."

Strongly disagree 1 ◯◯◯◯◯ 5 *Strongly agree*

Statement 5: "The use of electronic Human-Machine Interface (eHMI) by HAVs enhances my trust in their intentions."

Strongly disagree 1 ◯◯◯◯◯ 5 *Strongly agree*

Statement 6: "HAVs are more likely to follow traffic rules compared to human drivers."

Strongly disagree 1 ◯◯◯◯◯ 5 *Strongly agree*

Statement 7: "Predictable behaviour of autonomous vehicles is essential for socially compliant driving in mixed traffic environments."

Strongly disagree 1 ◯◯◯◯◯ 5 *Strongly agree*

Statement 8: "I feel more comfortable sharing the road with autonomous vehicles when their driving behaviour is predictable."

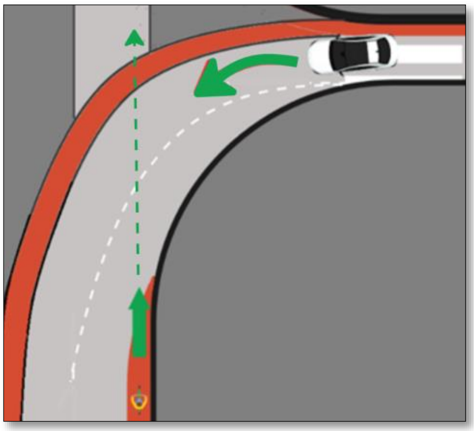
Strongly disagree 1 ◯◯◯◯◯ 5 *Strongly agree*

Scenario-based Questions

- **Deceleration at unsignalised intersection (clear deceleration, clear indication of HAV's intention) (Scenario 1/7)**

Imagine yourself cycling with the intention of moving straight in a shared roadway and an HAV is approaching the unsignalised intersection from the opposite direction.

The HAV is <u>clearly decelerating</u> and there is <u>a clear indication of its intention</u> to let you go first at the intersection. Please rank the following statements on a scale from 1 to 5:



Location: https://www.google.com/maps/place/52%C2%B004'48.9%22N+4%C2%B018'13.7%22E/@52.0802508,4.3031605,182m/data=!3m2!1e3!4b1!4m4!3m3!8m2!3d52.08025!4d4.3038056?hl=en&entry=ttu

- How much would you trust the HAV in this scenario would detect you and stop?

No trust 1 ◯◯◯◯◯ 5 *Complete trust*

- How would you rate the feeling of safety in this case?

Very unsafe 1 ◯◯◯◯◯ 5 *Very safe*

- To what extent do you consider this interaction as socially compliant?

Very unsocial 1 ◯◯◯◯◯ 5 *Very social*

- What would possibly be your potential reaction as a cyclist in this situation?

◯ Continue cycling at constant speed

◯ Brake

◯ Accelerate

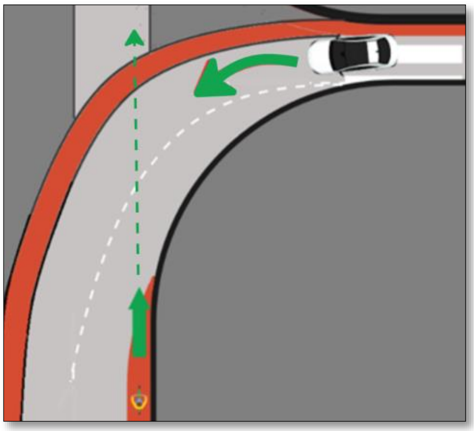
◯ Other

Please specify

- **Deceleration at unsignalised intersection (smooth deceleration, no clear HAV's indication of intention) (Scenario 2/7)**

Imagine yourself cycling with the intention of moving straight in a shared roadway and an HAV is approaching the unsignalised intersection from the opposite direction.

Now, the HAV is smoothly decelerating, but there is no clear indication of its intention at the intersection. Please rank the following statements on a scale from 1 to 5:

Location: https://www.google.com/maps/place/52%C2%B004'48.9%22N+4%C2%B018'13.7%22E/@52.0802508,4.3031605,182m/data=!3m2!1e3!4b1!4m4!3m3!8m2!3d52.08025!4d4.3038056?hl=en&entry=ttu

- How much would you trust the HAV in this scenario would detect you and stop?

No trust 1 ○○○○○ 5 *Complete trust*

- How would you rate the feeling of safety in this case?

Very unsafe 1 ○○○○○ 5 *Very safe*

- To what extent do you consider this interaction as socially compliant?

Very unsocial 1 ○○○○○ 5 *Very social*

- What would possibly be your potential reaction as a cyclist in this situation?

○ Continue cycling at constant speed

○ Brake

○ Accelerate

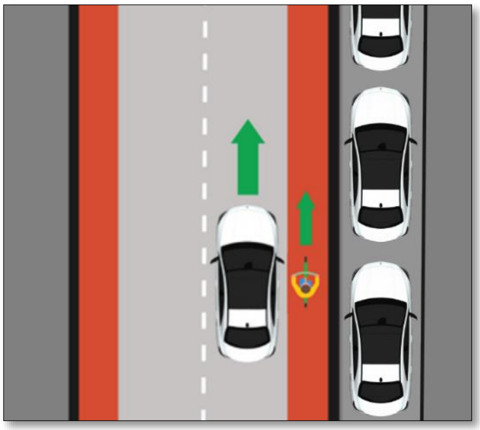
○ Other

Please specify

- **Constant speed of an HAV driving parallel to a cyclist on a straight road (Scenario 3/7)**

Imagine cycling on a straight road in a non-dedicated bicycle lane.

An HAV maintains a constant speed on a straight road.



Location: https://www.google.com/maps/place/52%C2%B005'03.4%22N+4%C2%B018'24.3%22E/@52.0842811,4.3041697,728m/data=!3m2!1e3!4b1!4m4!3m3!8m2!3d52.0842778!4d4.30675?hl=en&entry=ttu

- How does this impact your perceived safety as a cyclist?

Very unsafe 1 ◯◯◯◯◯ 5 *Very safe*

- How much do you trust the HAV to maintain its lane without violating the cyclist's space or leaning to the right?

No trust 1 ◯◯◯◯◯ 5 *Complete trust*

- To what extent do you consider this interaction as socially compliant?

Very unsocial 1 ◯◯◯◯◯ 5 *Very social*

- What would possibly be your potential reaction as a cyclist in this situation?

◯ Continue cycling at constant speed

◯ Brake

◯ Accelerate

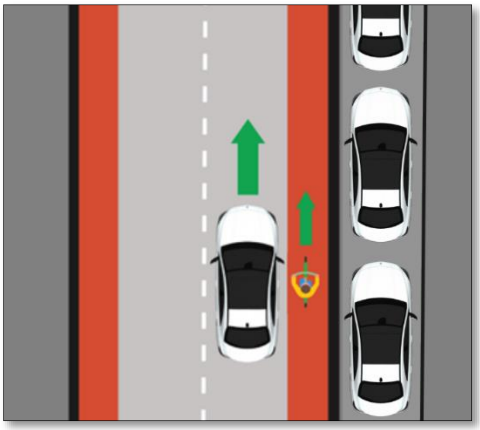
◯ Other

Please specify

- **Sudden acceleration of an HAV driving parallel to a cyclist on a straight road (Scenario 4/7)**

Imagine cycling on a straight road in a non-dedicated bicycle lane.

The HAV is abruptly accelerating on the straight road.



Location: https://www.google.com/maps/place/52%C2%B005'03.4%22N+4%C2%B018'24.3%22E/@52.0842811,4.3041697,728m/data=!3m2!1e3!4b1!4m4!3m3!8m2!3d52.0842778!4d4.30675?hl=en&entry=ttu

- How does this impact your perceived safety as a cyclist?

Very unsafe 1 ◯◯◯◯◯ 5 *Very safe*

- How much do you trust the HAV to maintain its lane without violating the cyclist's space or leaning to the right?

No trust 1 ◯◯◯◯◯ 5 *Complete trust*

- To what extent do you consider this interaction as socially compliant?

Very unsocial 1 ◯◯◯◯◯ 5 *Very social*

- What would possibly be your potential reaction as a cyclist in this situation?

◯ Continue cycling at constant speed

◯ Brake

◯ Accelerate

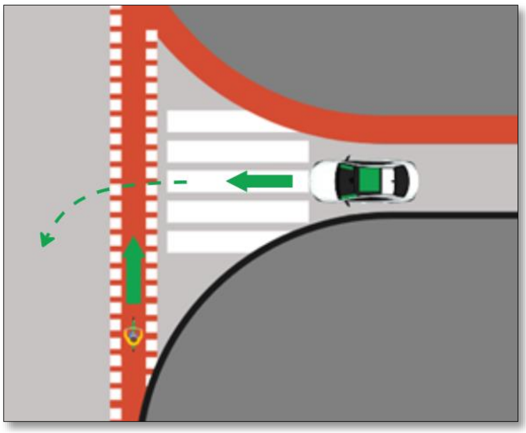
◯ Other

Please specify

- **Use of external Human-Machine Interface (eHMI) at intersections yielding priority to cyclist (Scenario 5/7)**

You are cycling in a non-dedicated bicycle lane. On the right side at the intersection, an HAV is using an eHMI to signal its intentions to take a left turn.

The HAV emitted a signal through the eHMI has stopped and is waiting for the cyclist to pass first.



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Location:
https://www.google.com/maps/place/52%C2%B004'53.3%22N+4%C2%B018'34.9%22E/@52.081473,4.3090493,182m/data=!3m2!1e3!4b1!4m4!3m3!8m2!3d52.0814722!4d4.3096944?hl=en&entry=ttu

- How much do you trust the HAV's use of eHMI to signal its intentions, considering your position in the non-dedicated bicycle lane?

No trust 1 ◯◯◯◯◯ 5 *Complete trust*

- How would you rate the feeling of safety in this case?

Very unsafe 1 ◯◯◯◯◯ 5 *Very safe*

- To what extent do you consider this interaction as socially compliant?

Very unsocial 1 ◯◯◯◯◯ 5 *Very social*

- What would possibly be your potential reaction as a cyclist in this situation?

◯ Continue cycling at constant speed

◯ Brake

◯ Accelerate

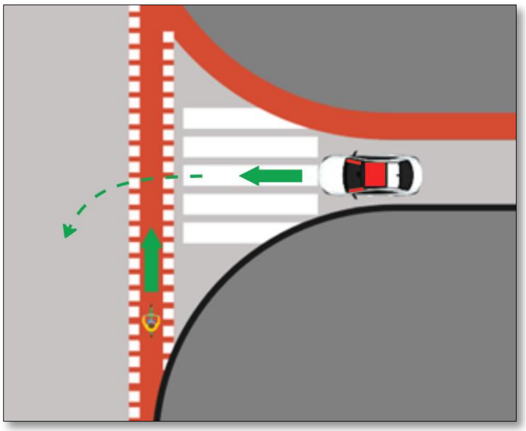
◯ Other

Please specify

- **Use of external Human-Machine Interface (eHMI) at intersections not yielding priority to cyclist (Scenario 6/7)**

You are cycling in a non-dedicated bicycle lane. On the right side at the intersection, an HAV is using an eHMI to signal its intentions to take a left turn.

The HAV emits a signal that <u>it is not going to wait for the cyclist to pass</u> and proceeds at the intersection having <u>constant speed</u>.

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<u>Location</u>: *https://www.google.com/maps/place/52%C2%B004'53.3%22N+4%C2%B018'34.9%22E/@52.081473,4.3090493,182m/data=!3m2!1e3!4b1!4m4!3m3!8m2!3d52.0814722!4d4.3096944?hl=en&entry=ttu*

- How much do you trust the HAV's use of eHMI to signal its intentions, considering your position in the non-dedicated bicycle lane?

No trust 1 ◯◯◯◯◯ 5 *Complete trust*

- How would you rate the feeling of safety in this case?

Very unsafe 1 ◯◯◯◯◯ 5 *Very safe*

- To what extent do you consider this interaction as socially compliant?

Very unsocial 1 ◯◯◯◯◯ 5 *Very social*

- What would possibly be your potential reaction as a cyclist in this situation?

◯ Continue cycling at constant speed

◯ Brake

◯ Accelerate

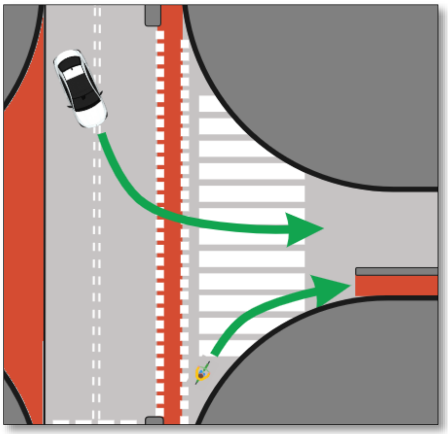
◯ Other

Please specify

- **Cyclist's response to HAV's deceleration when approaching from the opposite direction and turning left to continue alongside the cyclist (Scenario 7/7)**

Imagine you are cycling with the intention of making a right turn at an intersection.

An HAV is approaching from the opposite direction, slowing down before executing a left turn.

Location:
https://www.google.com/maps/place/52%C2%B004'46.3%22N+4%C2%B018'11.0%22E/@52.0796061,4.3019693,216m/data=!3m1!1e3!4m4!3m3!8m2!3d52.0795278!4d4.3030556?hl=en&entry=ttu

- How much do you trust the HAV's actions in slowing down before executing a left turn, considering your intention to make a right turn?

No trust 1 ◯◯◯◯◯ 5 *Complete trust*

- How would you rate the feeling of safety in this case?

Very unsafe 1 ◯◯◯◯◯ 5 *Very safe*

- To what extent do you consider this interaction as socially compliant?

Very unsocial 1 ◯◯◯◯◯ 5 *Very social*

- What would possibly be your potential reaction as a cyclist in this situation?

◯ Continue cycling at constant speed

◯ Brake

◯ Accelerate

◯ Other

Please specify

B. Bivariate correlation

Tables 13-21 present the findings from Bivariate Analysis. Specifically:

- Table 13 presents correlations between Trust vs HAV statements (Likert scale responses) across all scenarios
- Table 14 presents correlations between Perceived Safety vs HAV statements across all scenarios
- Table 15 presents correlations between Perceived Social Behaviour across all scenarios
- Table 16 presents correlations between Trust vs Demographics across all scenarios
- Table 17 presents correlations between Trust vs Age group_revised, Experience_revised and Frequency_revised across all scenarios
- Table 18 presents correlations between Perceived Safety vs Demographics across all scenarios
- Table 19 presents correlations between Perceived Safety vs Age group_revised, Experience_revised and Frequency_revised across all scenarios
- Table 20 presents correlations between Perceived Social Behaviour vs Demographics across all scenarios
- Table 21 presents correlations between Perceived Social Behaviour vs Age group_revised, Experience_revised and Frequency_revised across all scenarios

Statistically significant correlations (sig. < .05) are highlighted in yellow, meaning evidence of statistical significance that correlations are not due to chance.

It is worth noting that the highlighted purple correlations (in Tables 17, 19 & 21) between the revised Age group, Experience and Frequency variables for Trust, Perceived Safety and Perceived Social Behaviour do not reveal any medium-strong correlations across all scenarios. Their corresponding sig. values > 0.05 provide a test for the null hypothesis that the correlation coefficients in the population are indeed very low. Only the revised classification in Experience with AVs showed a small correlation (r = .273, p = .017) for Trust in scenario 6.

***Table 13**: Bivariate Correlation - Trust vs HAV statements*

Correlations

			Trust AVs prioritise cyclists	Belief in AVs communication	Confidence	Comfortability	eHMI	Rule compliance	Predictability	Share with AVs	Sc_1_trust	Sc_2_trust	Sc_3_trust	Sc_4_trust	Sc_5_trust	Sc_6_trust	Sc_7_trust
Spearman's rho	Trust AVs prioritise cyclists	Correlation Coefficient	1.000	.452**	.475**	.582**	.418**	.417**	0.146	0.169	.376**	.262*	.262*	0.174	.330**	0.070	.447**
		Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.208	0.144	0.001	0.022	0.022	0.132	0.004	0.547	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Belief in AVs communication	Correlation Coefficient	.452**	1.000	.537**	.548**	.532**	.281*	0.149	.278*	.246*	.315**	0.196	.302**	0.216	0.118	0.185
		Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.014	0.198	0.015	0.032	0.006	0.090	0.008	0.061	0.311	0.109
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Confidence	Correlation Coefficient	.475**	.537**	1.000	.578**	.407**	.371**	0.147	.249*	0.193	.350**	.338**	.312**	.363**	0.040	.350**
		Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.001	0.206	0.030	0.095	0.002	0.003	0.006	0.001	0.730	0.002
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Comfortability	Correlation Coefficient	.582**	.548**	.578**	1.000	.544**	.354**	0.016	.234*	.500**	.536**	.380**	.342**	.500**	0.162	.539**
		Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.002	0.891	0.041	0.000	0.000	0.001	0.003	0.000	0.162	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	eHMI	Correlation Coefficient	.418**	.532**	.407**	.544**	1.000	.383**	.345**	.440**	.395**	.315**	.422**	.268*	.526**	.328**	.345**
		Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.001	0.002	0.000	0.000	0.006	0.000	0.019	0.000	0.004	0.002
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Rule compliance	Correlation Coefficient	.417**	.281*	.371**	.354**	.383**	1.000	.385**	.405**	.377**	.267*	.376**	0.138	.472**	0.217	.387**
		Sig. (2-tailed)	0.000	0.014	0.001	0.002	0.001		0.001	0.000	0.001	0.020	0.001	0.235	0.000	0.059	0.001
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Predictability	Correlation Coefficient	0.146	0.149	0.147	0.016	.345**	.385**	1.000	.491**	0.198	0.015	.255*	.266*	.270*	0.188	0.157
		Sig. (2-tailed)	0.208	0.198	0.206	0.891	0.002	0.001		0.000	0.086	0.895	0.026	0.020	0.018	0.104	0.176
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Share with AVs	Correlation Coefficient	0.169	.278*	.249*	.234*	.440**	.405**	.491**	1.000	0.224	0.152	.384**	.368**	.376**	0.205	.286*
		Sig. (2-tailed)	0.144	0.015	0.030	0.041	0.000	0.000	0.000		0.052	0.191	0.001	0.001	0.001	0.076	0.012
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_1_trust	Correlation Coefficient	.376**	.246*	0.193	.500**	.395**	.377**	0.198	0.224	1.000	.516**	.441**	.303**	.553**	.462**	.328**
		Sig. (2-tailed)	0.001	0.032	0.095	0.000	0.000	0.001	0.086	0.052		0.000	0.000	0.008	0.000	0.000	0.004
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_2_trust	Correlation Coefficient	.262*	.315**	.350**	.536**	.315**	.267*	0.015	0.152	.516**	1.000	.329**	.341**	.323**	.387**	.409**
		Sig. (2-tailed)	0.022	0.006	0.002	0.000	0.006	0.020	0.895	0.191	0.000		0.004	0.003	0.004	0.001	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_3_trust	Correlation Coefficient	.262*	0.196	.338**	.380**	.422**	.376**	.255*	.384**	.441**	.329**	1.000	.620**	.575**	.240*	.561**
		Sig. (2-tailed)	0.022	0.090	0.003	0.001	0.000	0.001	0.026	0.001	0.000	0.004		0.000	0.000	0.037	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_4_trust	Correlation Coefficient	0.174	.302**	.312**	.342**	.268*	0.138	.266*	.368**	.303**	.341**	.620**	1.000	.412**	0.179	.294**
		Sig. (2-tailed)	0.132	0.008	0.006	0.003	0.019	0.235	0.020	0.001	0.008	0.003	0.000		0.000	0.121	0.010
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_5_trust	Correlation Coefficient	.330**	0.216	.363**	.500**	.526**	.472**	.270*	.376**	.553**	.323**	.575**	.412**	1.000	.306**	.416**
		Sig. (2-tailed)	0.004	0.061	0.001	0.000	0.000	0.000	0.018	0.001	0.000	0.004	0.000	0.000		0.007	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_6_trust	Correlation Coefficient	0.070	0.118	0.040	0.162	.328**	0.217	0.188	0.205	.462**	.387**	.240*	0.179	.306**	1.000	0.155
		Sig. (2-tailed)	0.547	0.311	0.730	0.162	0.004	0.059	0.104	0.076	0.000	0.001	0.037	0.121	0.007		0.180
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_7_trust	Correlation Coefficient	.447**	0.185	.350**	.539**	.345**	.387**	0.157	.286*	.328**	.409**	.561**	.294**	.416**	0.155	1.000
		Sig. (2-tailed)	0.000	0.109	0.002	0.000	0.002	0.001	0.176	0.012	0.004	0.000	0.000	0.010	0.000	0.180	
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 14*: Bivariate Correlation - Perceived Safety vs HAV statements*

Correlations

			Trust AVs prioritise cyclists	Belief in AVs communication	Confidence	Comfortability	eHMI	Rule compliance	Predictability	Share with AVs	Sc_1_safety	Sc_2_safety	Sc_3_safety	Sc_4_safety	Sc_5_safety	Sc_6_safety	Sc_7_safety
Spearman's rho	Trust AVs prioritise cyclists	Correlation Coefficient	1.000	.452**	.475**	.582**	.418**	.417**	0.146	0.169	.409**	.410**	-0.028	0.151	.341**	0.128	.335**
		Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.208	0.144	0.000	0.000	0.809	0.194	0.003	0.272	0.003
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Belief in AVs communication	Correlation Coefficient	.452**	1.000	.537**	.548**	.532**	.281*	0.149	.278*	.260*	.253*	0.124	.313**	.274*	0.154	0.088
		Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.014	0.198	0.015	0.023	0.027	0.285	0.006	0.016	0.183	0.450
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Confidence	Correlation Coefficient	.475**	.537**	1.000	.578**	.407**	.371**	0.147	.249*	.316**	.465**	.237*	.283*	.349**	0.077	.302**
		Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.001	0.206	0.030	0.005	0.000	0.039	0.013	0.002	0.507	0.008
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Comfortability	Correlation Coefficient	.582**	.548**	.578**	1.000	.544**	.354**	0.016	.234*	.584**	.604**	.258*	.226*	.449**	0.209	.326**
		Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.002	0.891	0.041	0.000	0.000	0.024	0.049	0.000	0.070	0.004
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	eHMI	Correlation Coefficient	.418**	.532**	.407**	.544**	1.000	.383**	.345**	.440**	.532**	.345**	.345**	0.205	.585**	0.222	.338**
		Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.001	0.002	0.000	0.000	0.002	0.002	0.076	0.000	0.054	0.003
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Rule compliance	Correlation Coefficient	.417**	.281*	.371**	.354**	.383**	1.000	.385**	.405**	.296**	.398**	0.095	0.168	.516**	0.110	.339**
		Sig. (2-tailed)	0.000	0.014	0.001	0.002	0.001		0.001	0.000	0.009	0.000	0.413	0.146	0.000	0.343	0.003
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Predictability	Correlation Coefficient	0.146	0.149	0.147	0.016	.345**	.385**	1.000	.491**	.227*	0.187	0.129	.275*	.294**	0.038	0.202
		Sig. (2-tailed)	0.208	0.198	0.206	0.891	0.002	0.001		0.000	0.048	0.105	0.268	0.016	0.010	0.744	0.080
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Share with AVs	Correlation Coefficient	0.169	.278*	.249*	.234*	.440**	.405**	.491**	1.000	.249*	0.216	0.148	0.224	.371**	0.195	.239*
		Sig. (2-tailed)	0.144	0.015	0.030	0.041	0.000	0.000	0.000		0.030	0.061	0.201	0.052	0.001	0.092	0.037
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_1_safety	Correlation Coefficient	.409**	.260*	.316**	.584**	.532**	.296**	.227*	.249*	1.000	.550**	.336**	0.161	.511**	.294**	.318**
		Sig. (2-tailed)	0.000	0.023	0.005	0.000	0.000	0.009	0.048	0.030		0.000	0.003	0.163	0.000	0.010	0.005
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_2_safety	Correlation Coefficient	.410**	.253*	.465**	.604**	.345**	.398**	0.187	0.216	.550**	1.000	0.196	.328**	.387**	.436**	.441**
		Sig. (2-tailed)	0.000	0.027	0.000	0.000	0.002	0.000	0.105	0.061	0.000		0.090	0.004	0.001	0.000	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_3_safety	Correlation Coefficient	-0.028	0.124	.237*	.258*	.345**	0.095	0.129	0.148	.336**	0.196	1.000	.440**	.310**	.241*	.281*
		Sig. (2-tailed)	0.809	0.285	0.039	0.024	0.002	0.413	0.268	0.201	0.003	0.090		0.000	0.006	0.036	0.014
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_4_safety	Correlation Coefficient	0.151	.313**	.283*	.226*	0.205	0.168	.275*	0.224	0.161	.328**	.440**	1.000	.333**	.280*	.244*
		Sig. (2-tailed)	0.194	0.006	0.013	0.049	0.076	0.146	0.016	0.052	0.163	0.004	0.000		0.003	0.014	0.034
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_5_safety	Correlation Coefficient	.341**	.274*	.349**	.449**	.585**	.516**	.294**	.371**	.511**	.387**	.310**	.333**	1.000	0.093	.438**
		Sig. (2-tailed)	0.003	0.016	0.002	0.000	0.000	0.000	0.010	0.001	0.000	0.001	0.006	0.003		0.425	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_6_safety	Correlation Coefficient	0.128	0.154	0.077	0.209	0.222	0.110	0.038	0.195	.294**	.436**	.241*	.280*	0.093	1.000	0.224
		Sig. (2-tailed)	0.272	0.183	0.507	0.070	0.054	0.343	0.744	0.092	0.010	0.000	0.036	0.014	0.425		0.052
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_7_safety	Correlation Coefficient	.335**	0.088	.302**	.326**	.338**	.339**	0.202	.239*	.318**	.441**	.281*	.244*	.438**	0.224	1.000
		Sig. (2-tailed)	0.003	0.450	0.008	0.004	0.003	0.003	0.080	0.037	0.005	0.000	0.014	0.034	0.000	0.052	
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

***Table 15**: Bivariate Correlation - Perceived Social Behaviour vs HAV statements*

Correlations

			Trust AVs prioritise cyclists	Belief in AVs communication	Confidence	Comfortability	eHMI	Rule compliance	Predictability	Share with AVs	Sc_1_social_comp	Sc_2_social_comp	Sc_3_social_comp	Sc_4_social_comp	Sc_5_social_comp	Sc_6_social_comp	Sc_7_social_comp
Spearman's rho	Trust AVs prioritise cyclists	Correlation Coefficient	1.000	.452**	.475**	.582**	.418**	.417**	0.146	0.169	.319**	0.187	0.144	0.171	.323**	-0.092	.298**
		Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.208	0.144	0.005	0.106	0.213	0.139	0.004	0.428	0.009
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Belief in AVs communication	Correlation Coefficient	.452**	1.000	.537**	.548**	.532**	.281*	0.149	.278*	0.168	0.032	0.111	.258*	0.097	0.062	0.091
		Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.014	0.198	0.015	0.148	0.784	0.341	0.025	0.407	0.594	0.435
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Confidence	Correlation Coefficient	.475**	.537**	1.000	.578**	.407**	.371**	0.147	.249*	0.130	0.056	.283*	.227*	.313**	-0.092	.292*
		Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.001	0.206	0.030	0.262	0.632	0.013	0.049	0.006	0.429	0.011
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Comfortability	Correlation Coefficient	.582**	.548**	.578**	1.000	.544**	.354**	0.016	.234*	.309**	.283*	.305**	.385**	.356**	0.058	.285*
		Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.002	0.891	0.041	0.007	0.013	0.007	0.001	0.002	0.617	0.013
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	eHMI	Correlation Coefficient	.418**	.532**	.407**	.544**	1.000	.383**	.345**	.440**	.339**	0.112	.388**	.245*	.479**	0.116	.338**
		Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.001	0.002	0.000	0.003	0.336	0.001	0.033	0.000	0.318	0.003
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Rule compliance	Correlation Coefficient	.417**	.281*	.371**	.354**	.383**	1.000	.385**	.405**	.316**	0.164	0.162	0.072	.488**	-0.072	.307**
		Sig. (2-tailed)	0.000	0.014	0.001	0.002	0.001		0.001	0.000	0.005	0.158	0.161	0.536	0.000	0.539	0.007
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Predictability	Correlation Coefficient	0.146	0.149	0.147	0.016	.345**	.385**	1.000	.491**	.292*	.234*	.254*	.259*	.421**	0.051	.303**
		Sig. (2-tailed)	0.208	0.198	0.206	0.891	0.002	0.001		0.000	0.010	0.042	0.027	0.024	0.000	0.664	0.008
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Share with AVs	Correlation Coefficient	0.169	.278*	.249*	.234*	.440**	.405**	.491**	1.000	0.171	-0.013	.245*	.240*	.375**	0.084	.292*
		Sig. (2-tailed)	0.144	0.015	0.030	0.041	0.000	0.000	0.000		0.140	0.909	0.033	0.036	0.001	0.472	0.010
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_1_social_comp	Correlation Coefficient	.319**	0.168	0.130	.309**	.339**	.316**	.292*	0.171	1.000	.309**	.258*	.260*	.465**	0.166	.297**
		Sig. (2-tailed)	0.005	0.148	0.262	0.007	0.003	0.005	0.010	0.140		0.007	0.024	0.023	0.000	0.152	0.009
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_2_social_comp	Correlation Coefficient	0.187	0.032	0.056	.283*	0.112	0.164	.234*	-0.013	.309**	1.000	0.177	.313**	0.164	0.145	.260*
		Sig. (2-tailed)	0.106	0.784	0.632	0.013	0.336	0.158	0.042	0.909	0.007		0.125	0.006	0.157	0.211	0.023
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_3_social_comp	Correlation Coefficient	0.144	0.111	.283*	.305**	.388**	0.162	.254*	.245*	.258*	0.177	1.000	.301**	.617**	0.189	.363**
		Sig. (2-tailed)	0.213	0.341	0.013	0.007	0.001	0.161	0.027	0.033	0.024	0.125		0.008	0.000	0.103	0.001
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_4_social_comp	Correlation Coefficient	0.171	.258*	.227*	.385**	.245*	0.072	.259*	.240*	.260*	.313**	.301**	1.000	0.183	.324**	0.113
		Sig. (2-tailed)	0.139	0.025	0.049	0.001	0.033	0.536	0.024	0.036	0.023	0.006	0.008		0.114	0.004	0.332
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_5_social_comp	Correlation Coefficient	.323**	0.097	.313**	.356**	.479**	.488**	.421**	.375**	.465**	0.164	.617**	0.183	1.000	0.014	.419**
		Sig. (2-tailed)	0.004	0.407	0.006	0.002	0.000	0.000	0.000	0.001	0.000	0.157	0.000	0.114		0.901	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_6_social_comp	Correlation Coefficient	-0.092	0.062	-0.092	0.058	0.116	-0.072	0.051	0.084	0.166	0.145	0.189	.324**	0.014	1.000	0.102
		Sig. (2-tailed)	0.428	0.594	0.429	0.617	0.318	0.539	0.664	0.472	0.152	0.211	0.103	0.004	0.901		0.382
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_7_social_comp	Correlation Coefficient	.298**	0.091	.292*	.285*	.338**	.307**	.303**	.292*	.297**	.260*	.363**	0.113	.419**	0.102	1.000
		Sig. (2-tailed)	0.009	0.435	0.011	0.013	0.003	0.007	0.008	0.010	0.009	0.023	0.001	0.332	0.000	0.382	
		N	76	76	76	76	76	76	76	76	76	76	76	76	76	76	76

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

***Table 16**: Bivariate Correlation - Trust vs Demographics*

Correlations

			Gender	Age Group	Frequency	Experience	Education	Familiarity	Sc_1_trust	Sc_2_trust	Sc_3_trust	Sc_4_trust	Sc_5_trust	Sc_6_trust	Sc_7_trust
Spearman's rho	Gender	Correlation Coefficient	1.000	-0.108	0.048	-0.087	0.119	0.016	-0.132	0.084	0.002	0.105	-0.009	-0.038	0.091
		Sig. (2-tailed)		0.354	0.684	0.453	0.306	0.889	0.257	0.470	0.987	0.366	0.938	0.744	0.434
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Age Group	Correlation Coefficient	-0.108	1.000	0.158	0.106	.282*	-0.080	-0.030	-0.140	-0.092	-0.117	-0.118	-0.022	-0.159
		Sig. (2-tailed)	0.354		0.173	0.364	0.014	0.495	0.799	0.227	0.430	0.316	0.308	0.850	0.169
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Frequency	Correlation Coefficient	0.048	0.158	1.000	.231*	.226*	0.016	0.042	0.151	-0.127	-0.133	-0.092	-0.156	0.131
		Sig. (2-tailed)	0.684	0.173		0.045	0.050	0.889	0.719	0.193	0.275	0.252	0.427	0.179	0.260
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Experience	Correlation Coefficient	-0.087	0.106	.231*	1.000	-0.108	-.349**	-0.044	-0.152	-0.061	0.009	-0.136	-.273*	0.080
		Sig. (2-tailed)	0.453	0.364	0.045		0.354	0.002	0.704	0.191	0.599	0.942	0.242	0.017	0.493
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Education	Correlation Coefficient	0.119	.282*	.226*	-0.108	1.000	-0.092	0.026	0.134	-0.046	-0.062	-0.092	0.128	0.020
		Sig. (2-tailed)	0.306	0.014	0.050	0.354		0.427	0.825	0.248	0.692	0.594	0.428	0.271	0.863
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Familiarity	Correlation Coefficient	0.016	-0.080	0.016	-.349**	-0.092	1.000	-0.104	0.138	0.155	0.179	0.003	-0.004	0.007
		Sig. (2-tailed)	0.889	0.495	0.889	0.002	0.427		0.370	0.234	0.180	0.121	0.979	0.971	0.952
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_1_trust	Correlation Coefficient	-0.132	-0.030	0.042	-0.044	0.026	-0.104	1.000	.516**	.441**	.303**	.553**	.462**	.328**
		Sig. (2-tailed)	0.257	0.799	0.719	0.704	0.825	0.370		0.000	0.000	0.008	0.000	0.000	0.004
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_2_trust	Correlation Coefficient	0.084	-0.140	0.151	-0.152	0.134	0.138	.516**	1.000	.329**	.341**	.323**	.387**	.409**
		Sig. (2-tailed)	0.470	0.227	0.193	0.191	0.248	0.234	0.000		0.004	0.003	0.004	0.001	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_3_trust	Correlation Coefficient	0.002	-0.092	-0.127	-0.061	-0.046	0.155	.441**	.329**	1.000	.620**	.575**	.240*	.561**
		Sig. (2-tailed)	0.987	0.430	0.275	0.599	0.692	0.180	0.000	0.004		0.000	0.000	0.037	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_4_trust	Correlation Coefficient	0.105	-0.117	-0.133	0.009	-0.062	0.179	.303**	.341**	.620**	1.000	.412**	0.179	.294**
		Sig. (2-tailed)	0.366	0.316	0.252	0.942	0.594	0.121	0.008	0.003	0.000		0.000	0.121	0.010
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_5_trust	Correlation Coefficient	-0.009	-0.118	-0.092	-0.136	-0.092	0.003	.553**	.323**	.575**	.412**	1.000	.306**	.416**
		Sig. (2-tailed)	0.938	0.308	0.427	0.242	0.428	0.979	0.000	0.004	0.000	0.000		0.007	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_6_trust	Correlation Coefficient	-0.038	-0.022	-0.156	-.273*	0.128	-0.004	.462**	.387**	.240*	0.179	.306**	1.000	0.155
		Sig. (2-tailed)	0.744	0.850	0.179	0.017	0.271	0.971	0.000	0.001	0.037	0.121	0.007		0.180
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_7_trust	Correlation Coefficient	0.091	-0.159	0.131	0.080	0.020	0.007	.328**	.409**	.561**	.294**	.416**	0.155	1.000
		Sig. (2-tailed)	0.434	0.169	0.260	0.493	0.863	0.952	0.004	0.000	0.000	0.010	0.000	0.180	
		N	76	76	76	76	76	76	76	76	76	76	76	76	76

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

__Table 17__: Bivariate Correlation - Trust vs Age Group Revised & Experience Revised & Frequency Revised

Correlations

			Age Group Revised	Exprerience_Rev	Frequency_Rev	Sc_1_trust	Sc_2_trust	Sc_3_trust	Sc_4_trust	Sc_5_trust	Sc_6_trust	Sc_7_trust
Spearman's rho	Age Group Revised	Correlation Coefficient	1.000	-0.094	-0.200	-0.014	-0.134	-0.076	-0.108	-0.103	-0.015	-0.148
		Sig. (2-tailed)		0.419	0.084	0.904	0.250	0.515	0.353	0.376	0.895	0.202
		N	76	76	76	76	76	76	76	76	76	76
	Exprerience_Rev	Correlation Coefficient	-0.094	1.000	0.218	0.044	0.152	0.061	-0.009	0.136	.273*	-0.080
		Sig. (2-tailed)	0.419		0.058	0.704	0.191	0.599	0.942	0.242	0.017	0.493
		N	76	76	76	76	76	76	76	76	76	76
	Frequency_Rev	Correlation Coefficient	-0.200	0.218	1.000	-0.045	-0.170	0.127	0.125	0.058	0.169	-0.122
		Sig. (2-tailed)	0.084	0.058		0.697	0.141	0.275	0.282	0.619	0.144	0.294
		N	76	76	76	76	76	76	76	76	76	76
	Sc_1_trust	Correlation Coefficient	-0.014	0.044	-0.045	1.000	.516**	.441**	.303**	.553**	.462**	.328**
		Sig. (2-tailed)	0.904	0.704	0.697		0.000	0.000	0.008	0.000	0.000	0.004
		N	76	76	76	76	76	76	76	76	76	76
	Sc_2_trust	Correlation Coefficient	-0.134	0.152	-0.170	.516**	1.000	.329**	.341**	.323**	.387**	.409**
		Sig. (2-tailed)	0.250	0.191	0.141	0.000		0.004	0.003	0.004	0.001	0.000
		N	76	76	76	76	76	76	76	76	76	76
	Sc_3_trust	Correlation Coefficient	-0.076	0.061	0.127	.441**	.329**	1.000	.620**	.575**	.240*	.561**
		Sig. (2-tailed)	0.515	0.599	0.275	0.000	0.004		0.000	0.000	0.037	0.000
		N	76	76	76	76	76	76	76	76	76	76
	Sc_4_trust	Correlation Coefficient	-0.108	-0.009	0.125	.303**	.341**	.620**	1.000	.412**	0.179	.294**
		Sig. (2-tailed)	0.353	0.942	0.282	0.008	0.003	0.000		0.000	0.121	0.010
		N	76	76	76	76	76	76	76	76	76	76
	Sc_5_trust	Correlation Coefficient	-0.103	0.136	0.058	.553**	.323**	.575**	.412**	1.000	.306**	.416**
		Sig. (2-tailed)	0.376	0.242	0.619	0.000	0.004	0.000	0.000		0.007	0.000
		N	76	76	76	76	76	76	76	76	76	76
	Sc_6_trust	Correlation Coefficient	-0.015	.273*	0.169	.462**	.387**	.240*	0.179	.306**	1.000	0.155
		Sig. (2-tailed)	0.895	0.017	0.144	0.000	0.001	0.037	0.121	0.007		0.180
		N	76	76	76	76	76	76	76	76	76	76
	Sc_7_trust	Correlation Coefficient	-0.148	-0.080	-0.122	.328**	.409**	.561**	.294**	.416**	0.155	1.000
		Sig. (2-tailed)	0.202	0.493	0.294	0.004	0.000	0.000	0.010	0.000	0.180	
		N	76	76	76	76	76	76	76	76	76	76

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 18: *Bivariate Correlation - Perceived Safety vs Demographics*

Correlations

			Gender	Age Group	Frequency	Experience	Education	Familiarity	Sc_1_safety	Sc_2_safety	Sc_3_safety	Sc_4_safety	Sc_5_safety	Sc_6_safety	Sc_7_safety
Spearman's rho	Gender	Correlation Coefficient	1.000	-0.108	0.048	-0.087	0.119	0.016	-0.111	0.036	0.054	-0.112	0.088	-0.047	0.018
		Sig. (2-tailed)		0.354	0.684	0.453	0.306	0.889	0.339	0.756	0.643	0.336	0.448	0.687	0.878
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Age Group	Correlation Coefficient	-0.108	1.000	0.158	0.106	.282*	-0.080	-0.062	-0.088	-0.099	-0.134	-0.030	-0.068	-0.088
		Sig. (2-tailed)	0.354		0.173	0.364	0.014	0.495	0.596	0.449	0.394	0.250	0.795	0.560	0.448
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Frequency	Correlation Coefficient	0.048	0.158	1.000	.231*	.226*	0.016	0.065	0.090	-0.171	-0.185	-0.074	-0.024	-0.069
		Sig. (2-tailed)	0.684	0.173		0.045	0.050	0.889	0.579	0.440	0.139	0.109	0.527	0.835	0.552
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Experience	Correlation Coefficient	-0.087	0.106	.231*	1.000	-0.108	-.349**	0.025	-0.117	-0.033	-0.119	-0.044	-0.027	-0.025
		Sig. (2-tailed)	0.453	0.364	0.045		0.354	0.002	0.828	0.315	0.777	0.306	0.707	0.816	0.829
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Education	Correlation Coefficient	0.119	.282*	.226*	-0.108	1.000	-0.092	-0.080	0.139	-0.193	0.025	0.002	0.085	0.035
		Sig. (2-tailed)	0.306	0.014	0.050	0.354		0.427	0.495	0.231	0.096	0.827	0.989	0.465	0.762
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Familiarity	Correlation Coefficient	0.016	-0.080	0.016	-.349**	-0.092	1.000	0.024	.239*	0.157	.226*	0.102	0.200	-0.037
		Sig. (2-tailed)	0.889	0.495	0.889	0.002	0.427		0.835	0.038	0.177	0.050	0.381	0.084	0.752
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_1_safety	Correlation Coefficient	-0.111	-0.062	0.065	0.025	-0.080	0.024	1.000	.550**	.336**	0.161	.511**	.294**	.318**
		Sig. (2-tailed)	0.339	0.596	0.579	0.828	0.495	0.835		0.000	0.003	0.163	0.000	0.010	0.005
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_2_safety	Correlation Coefficient	0.036	-0.088	0.090	-0.117	0.139	.239*	.550**	1.000	0.196	.328**	.387**	.436**	.441**
		Sig. (2-tailed)	0.756	0.449	0.440	0.315	0.231	0.038	0.000		0.090	0.004	0.001	0.000	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_3_safety	Correlation Coefficient	0.054	-0.099	-0.171	-0.033	-0.193	0.157	.336**	0.196	1.000	.440**	.310**	.241*	.281*
		Sig. (2-tailed)	0.643	0.394	0.139	0.777	0.096	0.177	0.003	0.090		0.000	0.006	0.036	0.014
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_4_safety	Correlation Coefficient	-0.112	-0.134	-0.185	-0.119	0.025	.226*	0.161	.328**	.440**	1.000	.333**	.280*	.244*
		Sig. (2-tailed)	0.336	0.250	0.109	0.306	0.827	0.050	0.163	0.004	0.000		0.003	0.014	0.034
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_5_safety	Correlation Coefficient	0.088	-0.030	-0.074	-0.044	0.002	0.102	.511**	.387**	.310**	.333**	1.000	0.093	.438**
		Sig. (2-tailed)	0.448	0.795	0.527	0.707	0.989	0.381	0.000	0.001	0.006	0.003		0.425	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_6_safety	Correlation Coefficient	-0.047	-0.068	-0.024	-0.027	0.085	0.200	.294**	.436**	.241*	.280*	0.093	1.000	0.224
		Sig. (2-tailed)	0.687	0.560	0.835	0.816	0.465	0.084	0.010	0.000	0.036	0.014	0.425		0.052
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_7_safety	Correlation Coefficient	0.018	-0.088	-0.069	-0.025	0.035	-0.037	.318**	.441**	.281*	.244*	.438**	0.224	1.000
		Sig. (2-tailed)	0.878	0.448	0.552	0.829	0.762	0.752	0.005	0.000	0.014	0.034	0.000	0.052	
		N	76	76	76	76	76	76	76	76	76	76	76	76	76

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

***Table 19**: Bivariate Correlation - Perceived Safety vs Age Group Revised & Experience Revised & Frequency Revised*

Correlations

			Age Group Revised	Exprerience_Rev	Frequency_Rev	Sc_1_safety	Sc_2_safety	Sc_3_safety	Sc_4_safety	Sc_5_safety	Sc_6_safety	Sc_7_safety
Spearman's rho	Age Group Revised	Correlation Coefficient	1.000	-0.094	-0.200	-0.047	-0.082	-0.095	-0.131	-0.014	-0.058	-0.071
		Sig. (2-tailed)		0.419	0.084	0.689	0.480	0.415	0.261	0.905	0.621	0.541
		N	76	76	76	76	76	76	76	76	76	76
	Exprerience_Rev	Correlation Coefficient	-0.094	1.000	0.218	-0.025	0.117	0.033	0.119	0.044	0.027	0.025
		Sig. (2-tailed)	0.419		0.058	0.828	0.315	0.777	0.306	0.707	0.816	0.829
		N	76	76	76	76	76	76	76	76	76	76
	Frequency_Rev	Correlation Coefficient	-0.200	0.218	1.000	-0.053	-0.114	0.168	0.129	0.048	0.063	0.063
		Sig. (2-tailed)	0.084	0.058		0.652	0.327	0.146	0.265	0.682	0.589	0.588
		N	76	76	76	76	76	76	76	76	76	76
	Sc_1_safety	Correlation Coefficient	-0.047	-0.025	-0.053	1.000	.550**	.336**	0.161	.511**	.294**	.318**
		Sig. (2-tailed)	0.689	0.828	0.652		0.000	0.003	0.163	0.000	0.010	0.005
		N	76	76	76	76	76	76	76	76	76	76
	Sc_2_safety	Correlation Coefficient	-0.082	0.117	-0.114	.550**	1.000	0.196	.328**	.387**	.436**	.441**
		Sig. (2-tailed)	0.480	0.315	0.327	0.000		0.090	0.004	0.001	0.000	0.000
		N	76	76	76	76	76	76	76	76	76	76
	Sc_3_safety	Correlation Coefficient	-0.095	0.033	0.168	.336**	0.196	1.000	.440**	.310**	.241*	.281*
		Sig. (2-tailed)	0.415	0.777	0.146	0.003	0.090		0.000	0.006	0.036	0.014
		N	76	76	76	76	76	76	76	76	76	76
	Sc_4_safety	Correlation Coefficient	-0.131	0.119	0.129	0.161	.328**	.440**	1.000	.333**	.280*	.244*
		Sig. (2-tailed)	0.261	0.306	0.265	0.163	0.004	0.000		0.003	0.014	0.034
		N	76	76	76	76	76	76	76	76	76	76
	Sc_5_safety	Correlation Coefficient	-0.014	0.044	0.048	.511**	.387**	.310**	.333**	1.000	0.093	.438**
		Sig. (2-tailed)	0.905	0.707	0.682	0.000	0.001	0.006	0.003		0.425	0.000
		N	76	76	76	76	76	76	76	76	76	76
	Sc_6_safety	Correlation Coefficient	-0.058	0.027	0.063	.294**	.436**	.241*	.280*	0.093	1.000	0.224
		Sig. (2-tailed)	0.621	0.816	0.589	0.010	0.000	0.036	0.014	0.425		0.052
		N	76	76	76	76	76	76	76	76	76	76
	Sc_7_safety	Correlation Coefficient	-0.071	0.025	0.063	.318**	.441**	.281*	.244*	.438**	0.224	1.000
		Sig. (2-tailed)	0.541	0.829	0.588	0.005	0.000	0.014	0.034	0.000	0.052	
		N	76	76	76	76	76	76	76	76	76	76

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 20: *Bivariate Correlation - Perceived Social Behaviour vs Demographics*

Correlations

			Gender	Age Group	Frequency	Experience	Education	Familiarity	Sc_1_social_comp	Sc_2_social_comp	Sc_3_social_comp	Sc_4_social_comp	Sc_5_social_comp	Sc_6_social_comp	Sc_7_social_comp
Spearman's rho	Gender	Correlation Coefficient	1.000	-0.108	0.048	-0.087	0.119	0.016	-0.148	0.100	0.062	0.023	0.163	0.011	0.152
		Sig. (2-tailed)		0.354	0.684	0.453	0.306	0.889	0.201	0.391	0.598	0.841	0.159	0.927	0.190
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Age Group	Correlation Coefficient	-0.108	1.000	0.158	0.106	.282*	-0.080	-0.101	-0.055	-0.091	0.001	-0.185	0.007	-0.123
		Sig. (2-tailed)	0.354		0.173	0.364	0.014	0.495	0.383	0.639	0.434	0.993	0.111	0.951	0.290
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Frequency	Correlation Coefficient	0.048	0.158	1.000	.231*	.226*	0.016	0.017	0.165	0.011	0.154	-0.105	-0.010	-0.026
		Sig. (2-tailed)	0.684	0.173		0.045	0.050	0.889	0.884	0.153	0.927	0.185	0.366	0.932	0.824
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Experience	Correlation Coefficient	-0.087	0.106	.231*	1.000	-0.108	-.349**	0.075	-0.052	-0.140	0.038	-0.009	-0.038	-0.002
		Sig. (2-tailed)	0.453	0.364	0.045		0.354	0.002	0.518	0.653	0.229	0.744	0.936	0.743	0.988
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Education	Correlation Coefficient	0.119	.282*	.226*	-0.108	1.000	-0.092	-0.087	0.191	-0.070	0.048	-0.114	0.024	-0.054
		Sig. (2-tailed)	0.306	0.014	0.050	0.354		0.427	0.454	0.099	0.549	0.683	0.328	0.835	0.644
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Familiarity	Correlation Coefficient	0.016	-0.080	0.016	-.349**	-0.092	1.000	-0.071	0.025	.291*	0.130	0.064	0.038	-0.108
		Sig. (2-tailed)	0.889	0.495	0.889	0.002	0.427		0.542	0.829	0.011	0.262	0.583	0.747	0.351
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_1_social_comp	Correlation Coefficient	-0.148	-0.101	0.017	0.075	-0.087	-0.071	1.000	.309**	.258*	.260*	.465**	0.166	.297**
		Sig. (2-tailed)	0.201	0.383	0.884	0.518	0.454	0.542		0.007	0.024	0.023	0.000	0.152	0.009
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_2_social_comp	Correlation Coefficient	0.100	-0.055	0.165	-0.052	0.191	0.025	.309**	1.000	0.177	.313**	0.164	0.145	.260*
		Sig. (2-tailed)	0.391	0.639	0.153	0.653	0.099	0.829	0.007		0.125	0.006	0.157	0.211	0.023
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_3_social_comp	Correlation Coefficient	0.062	-0.091	0.011	-0.140	-0.070	.291*	.258*	0.177	1.000	.301**	.617**	0.189	.363**
		Sig. (2-tailed)	0.598	0.434	0.927	0.229	0.549	0.011	0.024	0.125		0.008	0.000	0.103	0.001
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_4_social_comp	Correlation Coefficient	0.023	0.001	0.154	0.038	0.048	0.130	.260*	.313**	.301**	1.000	0.183	.324**	0.113
		Sig. (2-tailed)	0.841	0.993	0.185	0.744	0.683	0.262	0.023	0.006	0.008		0.114	0.004	0.332
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_5_social_comp	Correlation Coefficient	0.163	-0.185	-0.105	-0.009	-0.114	0.064	.465**	0.164	.617**	0.183	1.000	0.014	.419**
		Sig. (2-tailed)	0.159	0.111	0.366	0.936	0.328	0.583	0.000	0.157	0.000	0.114		0.901	0.000
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_6_social_comp	Correlation Coefficient	0.011	0.007	-0.010	-0.038	0.024	0.038	0.166	0.145	0.189	.324**	0.014	1.000	0.102
		Sig. (2-tailed)	0.927	0.951	0.932	0.743	0.835	0.747	0.152	0.211	0.103	0.004	0.901		0.382
		N	76	76	76	76	76	76	76	76	76	76	76	76	76
	Sc_7_social_comp	Correlation Coefficient	0.152	-0.123	-0.026	-0.002	-0.054	-0.108	.297**	.260*	.363**	0.113	.419**	0.102	1.000
		Sig. (2-tailed)	0.190	0.290	0.824	0.988	0.644	0.351	0.009	0.023	0.001	0.332	0.000	0.382	
		N	76	76	76	76	76	76	76	76	76	76	76	76	76

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

***Table 21**: Bivariate Correlation - Perceived Social Behaviour vs Age Group Revised & Experience Revised & Frequency Revised*

Correlations

			Age Group Revised	Exprerience_Rev	Frequency_Rev	Sc_1_social_comp	Sc_2_social_comp	Sc_3_social_comp	Sc_4_social_comp	Sc_5_social_comp	Sc_6_social_comp	Sc_7_social_comp
Spearman's rho	Age Group Revised	Correlation Coefficient	1.000	-0.094	-0.200	-0.088	-0.056	-0.078	0.006	-0.172	0.013	-0.100
		Sig. (2-tailed)		0.419	0.084	0.451	0.630	0.505	0.958	0.138	0.908	0.388
		N	76	76	76	76	76	76	76	76	76	76
	Exprerience_Rev	Correlation Coefficient	-0.094	1.000	0.218	-0.075	0.052	0.140	-0.038	0.009	0.038	0.002
		Sig. (2-tailed)	0.419		0.058	0.518	0.653	0.229	0.744	0.936	0.743	0.988
		N	76	76	76	76	76	76	76	76	76	76
	Frequency_Rev	Correlation Coefficient	-0.200	0.218	1.000	-0.004	-0.184	0.000	-0.172	0.114	0.032	0.037
		Sig. (2-tailed)	0.084	0.058		0.970	0.111	0.998	0.138	0.328	0.784	0.750
		N	76	76	76	76	76	76	76	76	76	76
	Sc_1_social_comp	Correlation Coefficient	-0.088	-0.075	-0.004	1.000	.309**	.258*	.260*	.465**	0.166	.297**
		Sig. (2-tailed)	0.451	0.518	0.970		0.007	0.024	0.023	0.000	0.152	0.009
		N	76	76	76	76	76	76	76	76	76	76
	Sc_2_social_comp	Correlation Coefficient	-0.056	0.052	-0.184	.309**	1.000	0.177	.313**	0.164	0.145	.260*
		Sig. (2-tailed)	0.630	0.653	0.111	0.007		0.125	0.006	0.157	0.211	0.023
		N	76	76	76	76	76	76	76	76	76	76
	Sc_3_social_comp	Correlation Coefficient	-0.078	0.140	0.000	.258*	0.177	1.000	.301**	.617**	0.189	.363**
		Sig. (2-tailed)	0.505	0.229	0.998	0.024	0.125		0.008	0.000	0.103	0.001
		N	76	76	76	76	76	76	76	76	76	76
	Sc_4_social_comp	Correlation Coefficient	0.006	-0.038	-0.172	.260*	.313**	.301**	1.000	0.183	.324**	0.113
		Sig. (2-tailed)	0.958	0.744	0.138	0.023	0.006	0.008		0.114	0.004	0.332
		N	76	76	76	76	76	76	76	76	76	76
	Sc_5_social_comp	Correlation Coefficient	-0.172	0.009	0.114	.465**	0.164	.617**	0.183	1.000	0.014	.419**
		Sig. (2-tailed)	0.138	0.936	0.328	0.000	0.157	0.000	0.114		0.901	0.000
		N	76	76	76	76	76	76	76	76	76	76
	Sc_6_social_comp	Correlation Coefficient	0.013	0.038	0.032	0.166	0.145	0.189	.324**	0.014	1.000	0.102
		Sig. (2-tailed)	0.908	0.743	0.784	0.152	0.211	0.103	0.004	0.901		0.382
		N	76	76	76	76	76	76	76	76	76	76
	Sc_7_social_comp	Correlation Coefficient	-0.100	0.002	0.037	.297**	.260*	.363**	0.113	.419**	0.102	1.000
		Sig. (2-tailed)	0.388	0.988	0.750	0.009	0.023	0.001	0.332	0.000	0.382	
		N	76	76	76	76	76	76	76	76	76	76

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

C. Normality Tests & Outliers

Trust

A non-significant result (Sig. value of more than .05) indicates normality. In this case, according to the Shapiro-Wilk test, Sig. < .0001, suggesting a violation of the assumption of normality.

***Table 22**: Tests of Normality for Trust*

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Sc_1_trust	.217	76	.000	.903	76	.000
Sc_2_trust	.256	76	.000	.871	76	.000
Sc_3_trust	.245	76	.000	.892	76	.000
Sc_4_trust	.191	76	.000	.913	76	.000
Sc_5_trust	.264	76	.000	.869	76	.000
Sc_6_trust	.206	76	.000	.898	76	.000
Sc_7_trust	.215	76	.000	.903	76	.000

a. Lilliefors Significance Correction

Outliers are shown on their respective boxes with their ID# per scenario for Trust.

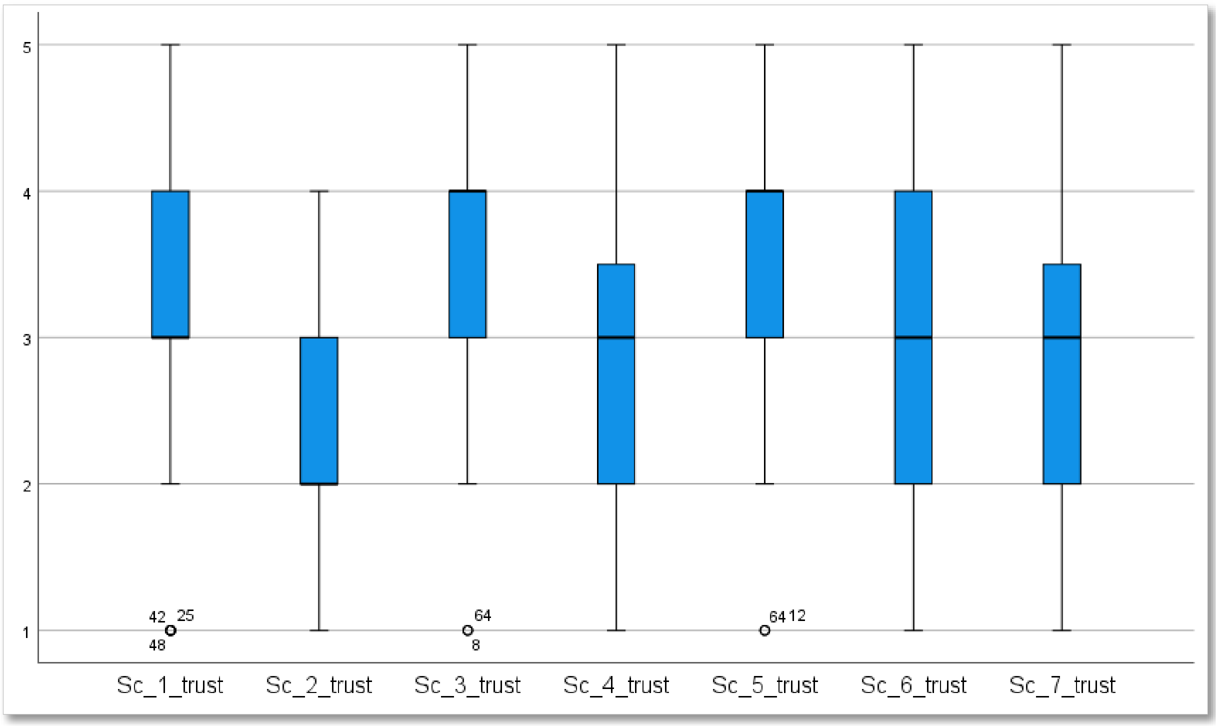


***Figure 13**: Boxplot of the distribution of scores of Trust for Scenarios 1 - 7*

Perceived safety

A non-significant result (Sig. value of more than .05) indicates normality. In this case, according to the Shapiro-Wilk test, Sig. < .0001, suggesting a violation of the assumption of normality.

***Table 23**: Tests of Normality for Perceived Safety*

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Sc_1_safety	.217	76	.000	.907	76	.000
Sc_2_safety	.251	76	.000	.864	76	.000
Sc_3_safety	.256	76	.000	.885	76	.000
Sc_4_safety	.199	76	.000	.906	76	.000
Sc_5_safety	.275	76	.000	.871	76	.000
Sc_6_safety	.180	76	.000	.895	76	.000
Sc_7_safety	.217	76	.000	.885	76	.000

a. Lilliefors Significance Correction

Outliers are shown on their respective boxes with their ID# per scenario for Perceived Safety.

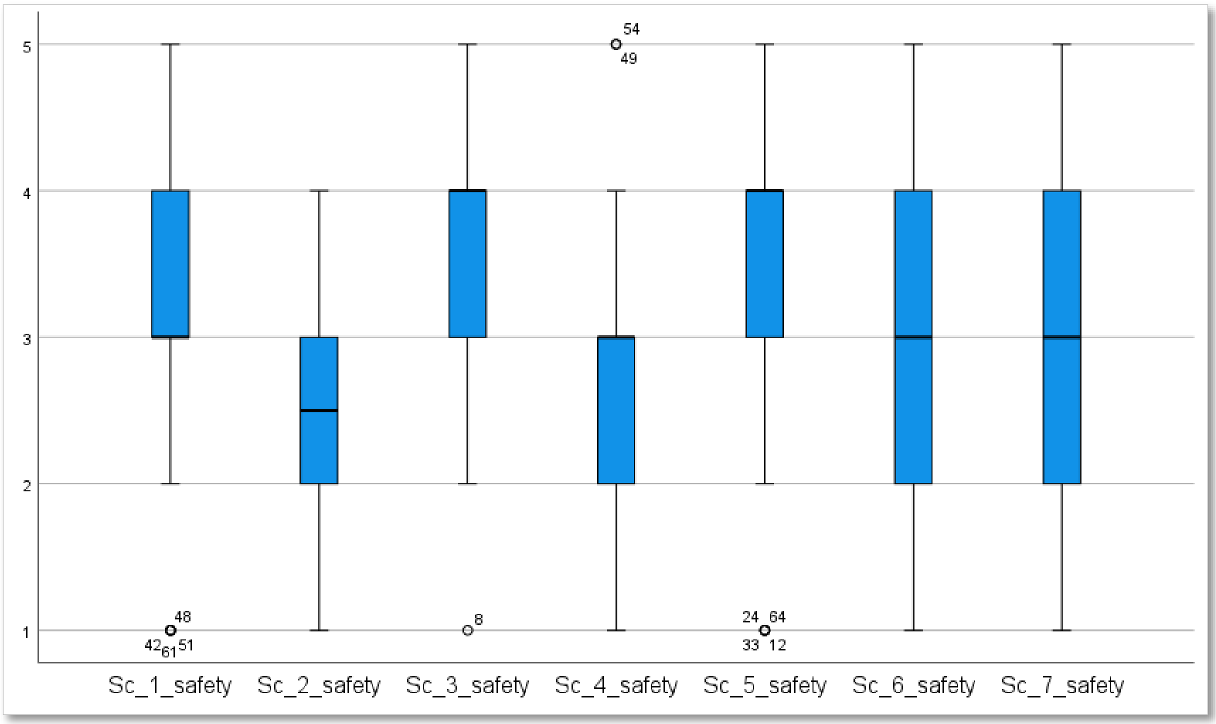


***Figure 14**: Boxplot of the distribution of scores of Perceived Safety for Scenarios 1 - 7*

Perceived social behaviour

A non-significant result (Sig. value of more than .05) indicates normality. In this case, according to the Shapiro-Wilk test, Sig. < .0001, suggesting a violation of the assumption of normality.

***Table 24**: Tests of Normality for Perceived Social Behaviour*

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Sc_1_social_comp	.216	76	.000	.894	76	.000
Sc_2_social_comp	.226	76	.000	.886	76	.000
Sc_3_social_comp	.233	76	.000	.897	76	.000
Sc_4_social_comp	.202	76	.000	.907	76	.000
Sc_5_social_comp	.260	76	.000	.833	76	.000
Sc_6_social_comp	.175	76	.000	.890	76	.000
Sc_7_social_comp	.241	76	.000	.834	76	.000

a. Lilliefors Significance Correction

Outliers are shown on their respective boxes with their ID# per scenario for Perceived Social Behaviour.

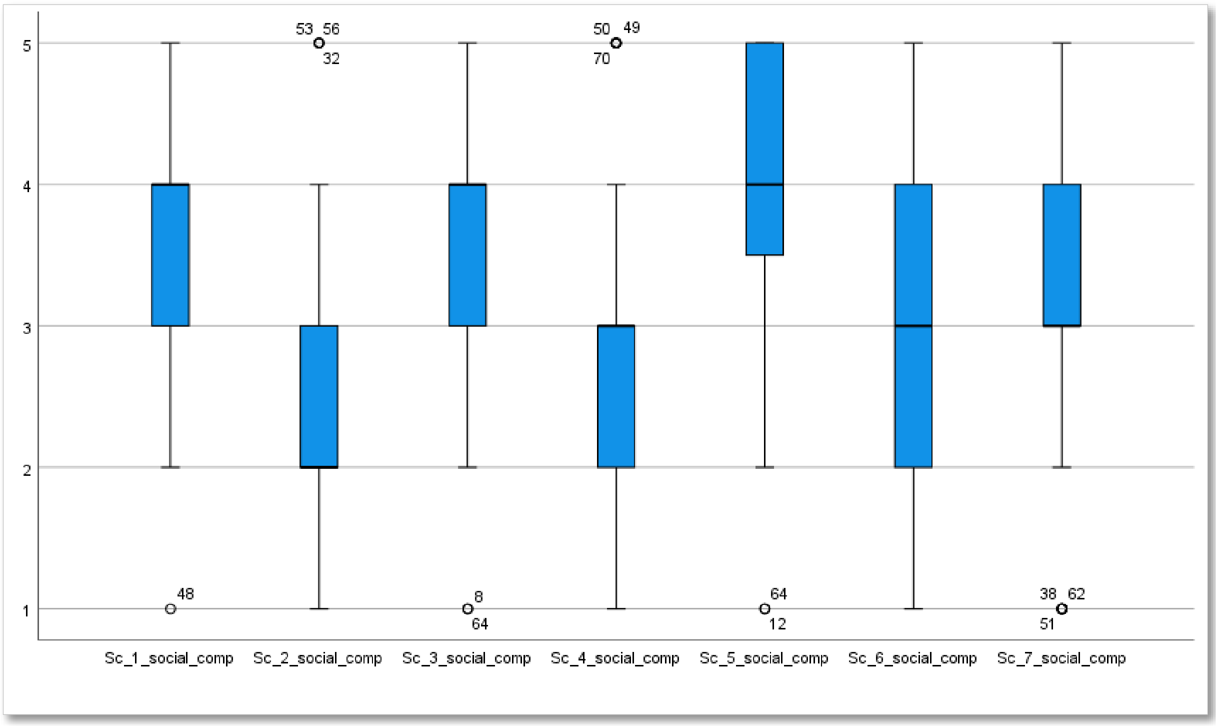


***Figure 15**: Boxplot of the distribution of scores of Perceived Social Behaviour for Scenarios 1-7*

D. Repeated Measures

Repeated Measures One-Way ANOVA requires a set of assumptions to hold. As highlighted by Muhammad (2023), these include:

1. The presence of a single dependent variable measured at a continuous level.
2. The inclusion of one within-subjects factor containing three or more categorical levels.
3. The absence of significant outliers across any level of the within-subjects factor.
4. The approximate normal distribution of the dependent variable within each level of the within-subjects factor.
5. Equality of variances (i.e., sphericity) among the differences across all combinations of levels within the within-subjects factor.

Regarding Assumption #1 the dependent variable can also be a scale variable, with Likert scale variables being accepted as long as they are on a scale (1-5 as in our case). Here, the dependent variables are Trust, Perceived Safety and Perceived Social Behaviour.

Assumption #2 is also satisfied.

Assumption #3 A data point is considered an outlier if it either sits on its own or as in Figures 6, 7 and 8 it is located 1.5 box lengths from the edge of the box. It is noted with an "o" in the Boxplot. If it is located more than 3 box lengths from the edge of the box, it is called an extreme outlier and is noted with an " * " in the box plot.

Regarding outliers, no extreme outliers were found. However, some outliers were found as follows:

Table 25*: Outliers with participant ID #*

	Trust	Perceived Safety	Perceived Social Behaviour
Scenario 1: Deceleration at unsignalised intersection (clear deceleration, clear indication of intention)	25, 42, 48	42, 48, 51, 61	48
Scenario 2: Deceleration at unsignalised intersection (smooth deceleration, no clear indication of intention)	-	-	32, 53, 56
Scenario 3: Constant speed on a straight road	8, 64	8	8, 64
Scenario 4: Sudden acceleration encounter on a straight road	-	49, 54	49, 50, 70
Scenario 5: Use of external Human-Machine Interface (eHMI) at intersections (cyclist prioritisation)	12, 64	12, 24, 33, 64	12, 64
Scenario 6: Use of external Human-Machine Interface (eHMI) at intersections (no cyclist prioritisation)	-	-	-
Scenario 7: Cyclist response to AV deceleration	-	-	38, 51, 62

For Assumption #4 The scores appear to be skewed either positively or negatively. The Shapiro-Wilks tests indicate non-normality (sig <.001). However, this does not indicate a problem with the scale. It reflects the underlying nature of the questionnaire.

Taking the above into account, outliers could be removed from the data, or the data could be modified, as no errors were imported into the SPSS data file. However, the choice is made to accept the data and proceed with the Repeated Measures One-Way ANOVA since ANOVA is lenient to minor deviations from the assumptions.

Assumption #5 relates to sphericity and Mauchly's test of sphericity will be performed to validate sphericity.

Repeated Measures One-Way ANOVA was employed for each dependent variable (Trust, Perceived Safety and Perceived Social Behaviour) independently of any demographic variables. This approach investigated how each dependent variable varied from scenario to scenario.

Trust

Repeated Measures One-Way ANOVA was run on Trust as the only variable for each of the seven (7) scenarios. The sphericity assumption requires that the variance of the population difference scores for any two conditions are the same as that for any other two conditions.

To test this assumption, Mauchly's test of sphericity is run and revealed that the sphericity assumption has been violated (sig < .0001) and the test is statistically significant (*if sig <.05 the assumption of sphericity is statistically significant*). Thus, the null hypothesis is rejected and the alternative hypothesis is accepted, indicating that the population means are not equal.

***Table 26**: Mauchly's Test of Sphericity - Trust*

Measure: MEASURE_1							
Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon: Greenhouse-Geisser	Epsilon: Huynh-Feldt	Epsilon: Lower-bound
Trust	.377	71.017	20	.000	.745	.798	.167

Here is a summary of the findings:

- The sphericity hypothesis was invalidated, as evidenced by Mauchly's test of sphericity (Sig < .0001).
- Since the sphericity hypothesis was invalidated, the Greenhouse-Geisser metric is taken into account..

According to Cohen (1988), the following serves as a guideline:

- Effect size: small: Cohen's d (standard units) .2
- Effect size: medium: Cohen's d (standard units) .5
- Effect size: large: Cohen's d (standard units) .8

***Table 27**: Tests of Within-Subjects Effects - Trust*

Measure: MEASURE_1							
Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Trust	Sphericity Assumed	82.470	6	13.745	20.809	.000	.217
	Greenhouse-Geisser	82.470	4.470	18.449	20.809	.000	.217
	Huynh-Feldt	82.470	4.789	17.222	20.809	.000	.217
	Lower-bound	82.470	1.000	82.470	20.809	.000	.217
Error(Trust)	Sphericity Assumed	297.244	450	.661			
	Greenhouse-Geisser	297.244	335.268	.887			
	Huynh-Feldt	297.244	359.144	.828			
	Lower-bound	297.244	75.000	3.963			

Since the assumption of sphericity has been violated, it can be concluded that the Repeated Measures One-Way ANOVA is biased because it too easily returns a statistically significant result. Hence, a correction needs to be made to correct this bias by adjusting the degrees of freedom used in calculating the sig. value. The sample effect size based on within-subjects factor variability is called Partial Eta Squared, $\eta^2 = .217$, meaning small to medium effect.

> ***Note**: The result means that the scenarios elicited statistical changes in Trust, $F(6, 450) = 20.809$, partial $\eta^2 = .217$.*

From pairwise comparisons, significant differences are sought (with significance <.05). All those are highlighted in yellow. Negative values in the Mean-Difference-column mean lower mean vs the mean it is compared to. For example, Sc_2_Trust mean is lower than Sc_1_Trust (difference at -0.789).

The Pairwise Comparisons Table 28, on the following page, shows significant differences between scenarios. Noteworthy differences were observed in the following comparisons:

- Between Scenario 1 and Scenario 2 (p < .0001)
- Between Scenario 1 and Scenario 5 (p = .0001)
- Among Scenario 2 and Scenarios 3, 5, 6, 7
- Among Scenario 3 and Scenarios 4, 7
- Between Scenario 4 and Scenario 5
- Among Scenario 5 and Scenarios 6, 7.

***Table 28**: Pairwise Comparisons - Trust*

Measure: MEASURE_1

(I) Trust	(J) Trust	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
1	2	.789*	.108	.000	.449	1.130
	3	-.250	.117	.759	-.618	.118
	4	.382	.140	.169	-.059	.822
	5	-.513*	.105	.000	-.844	-.183
	6	.118	.143	1.000	-.330	.567
	7	.250	.129	1.000	-.154	.654
2	1	-.789*	.108	.000	-1.130	-.449
	3	-1.039*	.125	.000	-1.432	-.647
	4	-.408	.133	.062	-.825	.009
	5	-1.303*	.121	.000	-1.685	-.921
	6	-.671*	.147	.000	-1.133	-.209
	7	-.539*	.116	.000	-.905	-.174
3	1	.250	.117	.759	-.118	.618
	2	1.039*	.125	.000	.647	1.432
	4	.632*	.102	.000	.310	.953
	5	-.263	.100	.213	-.577	.051
	6	.368	.163	.563	-.145	.881
	7	.500*	.105	.000	.169	.831
4	1	-.382	.140	.169	-.822	.059
	2	.408	.133	.062	-.009	.825
	3	-.632*	.102	.000	-.953	-.310
	5	-.895*	.122	.000	-1.279	-.510
	6	-.263	.176	1.000	-.817	.291
	7	-.132	.141	1.000	-.574	.311
5	1	.513*	.105	.000	.183	.844
	2	1.303*	.121	.000	.921	1.685
	3	.263	.100	.213	-.051	.577
	4	.895*	.122	.000	.510	1.279
	6	.632*	.152	.002	.154	1.110
	7	.763*	.114	.000	.405	1.121
6	1	-.118	.143	1.000	-.567	.330
	2	.671*	.147	.000	.209	1.133
	3	-.368	.163	.563	-.881	.145
	4	.263	.176	1.000	-.291	.817
	5	-.632*	.152	.002	-1.110	-.154
	7	.132	.171	1.000	-.406	.669
7	1	-.250	.129	1.000	-.654	.154
	2	.539*	.116	.000	.174	.905

3	-.500*	.105	.000	-.831	-.169
4	.132	.141	1.000	-.311	.574
5	-.763*	.114	.000	-1.121	-.405
6	-.132	.171	1.000	-.669	.406

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Perceived safety

The same analysis as above holds for Perceived Safety.

***Table 29**: Mauchly's Test of Sphericity - Perceived Safety*

Measure: MEASURE_1							
Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Safety	.472	54.649	20	.000	.817	.881	.167

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.
a. Design: Intercept
Within Subjects Design: Safety
b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

The sphericity hypothesis for Perceived Safety is rejected based on Mauchly's Test of Sphericity (Sig < .0001).

The sphericity assumption requires that the variance of the population difference scores for any two conditions are the same as the variance of the population difference scores for any other two conditions. This is reflected in the significance level (sig.). If sig. < .05, then the sphericity hypothesis is rejected, therefore, there is a difference in variance levels.

Since the sphericity hypothesis was invalidated, the Greenhouse-Geisser metric is taken into account (*see Tests of Within-Subjects Effects*) since sig. <.05, the confidence level is not equivalent to the 7 scenarios. Since Partial Eta Squared = .238, it means small to medium effect.

***Table 30**: Tests of Within-Subjects Effects - Perceived Safety*

Tests of Within-Subjects Effects

Measure: MEASURE_1							
Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Safety	Sphericity Assumed	100.128	6	16.688	23.435	.000	.238
	Greenhouse-Geisser	100.128	4.900	20.436	23.435	.000	.238
	Huynh-Feldt	100.128	5.283	18.951	23.435	.000	.238
	Lower-bound	100.128	1.000	100.128	23.435	.000	.238

Error(Safety)	Sphericity Assumed	320.444	450	.712
	Greenhouse-Geisser	320.444	367.470	.872
	Huynh-Feldt	320.444	396.256	.809
	Lower-bound	320.444	75.000	4.273

***Note**: The result means that the scenarios elicited statistical changes in Trust, F(6, 450) = 23.435, partial η^2 = .238.*

***Table 31**: Pairwise Comparisons - Perceived Safety*

Measure: MEASURE_1

(I) Safety	(J) Safety	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
1	2	.763*	.104	.000	.436	1.090
	3	-.382	.134	.117	-.802	.039
	4	.566*	.151	.008	.090	1.042
	5	-.408*	.126	.037	-.804	-.012
	6	.539*	.154	.016	.056	1.023
	7	.263	.133	1.000	-.155	.681
2	1	-.763*	.104	.000	-1.090	-.436
	3	-1.145*	.132	.000	-1.560	-.729
	4	-.197	.128	1.000	-.601	.207
	5	-1.171*	.126	.000	-1.568	-.774
	6	-.224	.126	1.000	-.621	.174
	7	-.500*	.107	.000	-.836	-.164
3	1	.382	.134	.117	-.039	.802
	2	1.145*	.132	.000	.729	1.560
	4	.947*	.115	.000	.585	1.310
	5	-.026	.138	1.000	-.459	.406
	6	.921*	.151	.000	.447	1.395
	7	.645*	.131	.000	.234	1.056
4	1	-.566*	.151	.008	-1.042	-.090
	2	.197	.128	1.000	-.207	.601
	3	-.947*	.115	.000	-1.310	-.585
	5	-.974*	.141	.000	-1.418	-.529
	6	-.026	.156	1.000	-.516	.463

	7	-.303	.143	.782	-.751	.146
5	1	.408*	.126	.037	.012	.804
	2	1.171*	.126	.000	.774	1.568
	3	.026	.138	1.000	-.406	.459
	4	.974*	.141	.000	.529	1.418
	6	.947*	.177	.000	.392	1.503
	7	.671*	.126	.000	.274	1.068
6	1	-.539*	.154	.016	-1.023	-.056
	2	.224	.126	1.000	-.174	.621
	3	-.921*	.151	.000	-1.395	-.447
	4	.026	.156	1.000	-.463	.516
	5	-.947*	.177	.000	-1.503	-.392
	7	-.276	.154	1.000	-.761	.208
7	1	-.263	.133	1.000	-.681	.155
	2	.500*	.107	.000	.164	.836
	3	-.645*	.131	.000	-1.056	-.234
	4	.303	.143	.782	-.146	.751
	5	-.671*	.126	.000	-1.068	-.274
	6	.276	.154	1.000	-.208	.761

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

From the Pairwise Comparisons analysis, significant differences in safety levels are observed:

- Between scenario 1 and scenarios 2, 4, 5 and 6, indicating higher safety in scenario 1 compared to scenarios 2, 4 and 6, but lower Perceived Safety compared to scenario 5.
- Between scenario 2 and scenarios 1, 3, 5 and 7, revealing lower Perceived Safety in scenario 2 compared to scenarios 1, 3, 5 and 7.
- Between scenario 3 and scenarios 2, 4, 6 and 7, show higher Perceived Safety in scenario 3 compared to scenarios 2, 4, 6 and 7.
- Between scenario 4 and scenarios 1, 3 and 5, indicating lower Perceived Safety in scenario 4 compared to scenarios 1, 3 and 5.
- Between scenario 5 and scenarios 1, 2, 4, 6 and 7, indicating higher Perceived Safety in scenario 5 compared to scenarios 1, 2, 4, 6 and 7.
- Between scenario 6 and scenarios 1, 3 and 5, revealing lower Perceived Safety in scenario 6 compared to scenarios 1, 3 and 5.
- Between scenario 7 and scenarios 2, 3 and 5, show lower Perceived Safety in scenario 7 compared to scenarios 3 and 5, but higher safety compared to scenario 2.

Perceived social behaviour

The same analysis as above holds for Perceived Social Behaviour.

Table 32*: Mauchly's Test of Sphericity - Perceived Social Behaviour*

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b] Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Soc_Comp	.532	45.900	20	.001	.824	.889	.167

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.
a. Design: Intercept
Within Subjects Design: Soc_Comp
b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

The hypothesis of sphericity is rejected for Perceived Social Behaviour (Soc_Comp Sig = .001) based on Mauchly's Test of Sphericity.

Subsequently, employing the Greenhouse-Geisser correction, a significant effect of the scenarios on Social Behaviour is observed ($p < .0001$, Partial Eta Squared = .265).

Table 33*: Tests of Within-Subjects Effects - Perceived Social Behaviour*

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Soc_Comp	Sphericity Assumed	131.274	6	21.879	26.994	.000	.265
	Greenhouse-Geisser	131.274	4.942	26.565	26.994	.000	.265
	Huynh-Feldt	131.274	5.332	24.619	26.994	.000	.265
	Lower-bound	131.274	1.000	131.274	26.994	.000	.265
Error(Soc_Comp)	Sphericity Assumed	364.726	450	.811			
	Greenhouse-Geisser	364.726	370.628	.984			
	Huynh-Feldt	364.726	399.920	.912			
	Lower-bound	364.726	75.000	4.863			

> ***Note**: The result means that the scenarios elicited statistical changes in Trust, $F(6, 450) = 26.994$, partial $\eta^2 = .265$.*

***Table 34**: Pairwise Comparisons - Perceived Social Behaviour*

Measure: MEASURE_1

(I) Soc_Comp	(J) Soc_Comp	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
1	2	1.053*	.127	.000	.654	1.452
	3	.079	.141	1.000	-.365	.523
	4	.868*	.147	.000	.407	1.330
	5	-.382*	.117	.035	-.749	-.014
	6	.855*	.166	.000	.333	1.378
	7	.368	.131	.131	-.043	.780
2	1	-1.053*	.127	.000	-1.452	-.654
	3	-.974*	.144	.000	-1.426	-.521
	4	-.184	.145	1.000	-.639	.271
	5	-1.434*	.142	.000	-1.880	-.988
	6	-.197	.164	1.000	-.714	.320
	7	-.684*	.134	.000	-1.106	-.263
3	1	-.079	.141	1.000	-.523	.365
	2	.974*	.144	.000	.521	1.426
	4	.789*	.143	.000	.340	1.239
	5	-.461*	.110	.002	-.806	-.115
	6	.776*	.168	.000	.247	1.305
	7	.289	.127	.530	-.109	.688
4	1	-.868*	.147	.000	-1.330	-.407
	2	.184	.145	1.000	-.271	.639
	3	-.789*	.143	.000	-1.239	-.340
	5	-1.250*	.151	.000	-1.725	-.775
	6	-.013	.159	1.000	-.515	.488
	7	-.500*	.155	.039	-.988	-.012
5	1	.382*	.117	.035	.014	.749
	2	1.434*	.142	.000	.988	1.880
	3	.461*	.110	.002	.115	.806
	4	1.250*	.151	.000	.775	1.725
	6	1.237*	.181	.000	.666	1.808
	7	.750*	.117	.000	.382	1.118
6	1	-.855*	.166	.000	-1.378	-.333
	2	.197	.164	1.000	-.320	.714

	3	-.776*	.168	.000	-1.305	-.247
	4	.013	.159	1.000	-.488	.515
	5	-1.237*	.181	.000	-1.808	-.666
	7	-.487	.171	.120	-1.025	.051
7	1	-.368	.131	.131	-.780	.043
	2	.684*	.134	.000	.263	1.106
	3	-.289	.127	.530	-.688	.109
	4	.500*	.155	.039	.012	.988
	5	-.750*	.117	.000	-1.118	-.382
	6	.487	.171	.120	-.051	1.025

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

From the Pairwise Comparisons analysis, significant differences in social levels are identified:

- Between scenario 1 and scenarios 2, 4, 5 and 6, indicating higher Perceived Social Behaviour levels in scenario 1 compared to scenarios 2, 4 and 6, but lower Perceived Social Behaviour levels compared to scenario 5.
- Between scenario 2 and scenarios 1, 3, 5 and 7, revealing lower Perceived Social Behaviour levels in scenario 2 compared to scenarios 1, 3, 5 and 7.
- Between scenario 3 and scenarios 2, 4, 5 and 6, show higher Perceived Social Behaviour levels compared to scenarios 2, 4 and 6, but lower Perceived Social Behaviour levels compared to scenario 5.
- Between scenario 4 and scenarios 1, 3, 5 and 7, indicating lower Perceived Social Behaviour levels in scenario 4 compared to scenarios 1, 3, 5 and 7.
- Between scenario 5 and all other scenarios, demonstrating higher Perceived Social Behaviour levels in scenario 5 compared to all other scenarios.
- Between scenario 6 and scenarios 1, 3 and 5 reveal lower Perceived Social Behaviour levels in scenario 6 compared to scenarios 1, 3 and 5.
- Between scenario 7 and scenarios 2, 4 and 5, showing higher Perceived Social Behaviour levels compared to scenarios 2 and 4, but lower compared to scenario 5.

In the following, additional factors are introduced with the aim of exploring their influence on the dependent parameters - Trust, Perceived Safety and Perceived Social Behaviour.

The following factors have been chosen according to their correlation to the dependent parameters. Their selection was based on the tables in Appendix B: Bivariate correlation.

- eHMI
- Rule Compliance
- Comfortability in sharing the roads with AVs
- Frequency of cycling (revised)

Trust × eHMI trust enhancement × Rule Compliance of AVs × Comfortability in sharing the roads with AVs × Frequency of cycling

The sphericity hypothesis for Trust is rejected based on Mauchly's Test of Sphericity (Sig < .001). As mentioned before, the sphericity assumption requires that the variance of the population difference scores for any two conditions is the same as the variance of the population difference scores for any other two conditions. This is reflected in the significance level (sig.). If sig. < .05, then the sphericity hypothesis is rejected, therefore, there is a difference in variance levels.

Table 35*: Mauchly's Test of Sphericity - Trust × eHMI trust enhancement × Rule compliance of AVs × Comfortability in sharing the roads with AVs × Frequency of cycling*

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Scenario_Trust	0.408	52.752	20	< .001	0.772	1.000	0.167

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + eHMI + Rulecompliance + Comfortability + Frequency_Rev
Within Subjects Design: Scenario_Trust

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Since the sphericity hypothesis was invalidated, the Greenhouse-Geisser metric is taken into account (*see Tests of Within-Subjects Effects below*).

It can be seen that the scenario given the set of factors to explore does not significantly interact with Trust as much (sig. = 0.168, partial Eta = 0.025, Effect size is very small << 0.2).

Comfortability with sharing the roads with AVs does significantly interact with Trust (sig. 0.001, partial Eta = 0.134) exhibiting a small effect.

The Tests of Within-Subjects Effects table indicates that Comfortability in sharing the roads with AVs significantly interacts with Scenario (sig. = .001).
Conversely, the type of scenario does not significantly influence Trust (p = 0.168).
The same holds for eHMI (p = 0.074), Rule Compliance (p = 0.081) and Frequency of cycling (p = 0.131) as their interaction with the scenario does not seem significant.

***Table 36**: Tests of Trust × eHMI trust enhancement × Rule Compliance of AVs × Comfortability in sharing the roads with AVs × Frequency of cycling*

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Scenario_Trust	Sphericity Assumed	5.706	6	0.951	1.59	0.149	0.025
	Greenhouse-Geisser	5.706	4.635	1.231	1.59	0.168	0.025
	Huynh-Feldt	5.706	6	0.951	1.59	0.149	0.025
	Lower-bound	5.706	1	5.706	1.59	0.212	0.025
Scenario_Trust * eHMI	Sphericity Assumed	22.081	24	0.92	1.54	0.053	0.092
	Greenhouse-Geisser	22.081	18.538	1.191	1.54	0.074	0.092
	Huynh-Feldt	22.081	24	0.92	1.54	0.053	0.092
	Lower-bound	22.081	4	5.52	1.54	0.203	0.092
Scenario_Trust * Rulecompliance	Sphericity Assumed	21.783	24	0.908	1.52	0.058	0.09
	Greenhouse-Geisser	21.783	18.538	1.175	1.52	0.081	0.09
	Huynh-Feldt	21.783	24	0.908	1.52	0.058	0.09
	Lower-bound	21.783	4	5.446	1.52	0.209	0.09
Scenario_Trust * Comfortability	Sphericity Assumed	34.026	24	1.418	2.37	0.000	0.134
	Greenhouse-Geisser	34.026	18.538	1.835	2.37	0.001	0.134
	Huynh-Feldt	34.026	24	1.418	2.37	0.000	0.134

	Lower-bound	34.026	4	8.507	2.37	0.062	0.134
Scenario_Trust * Frequency_Rev	Sphericity Assumed	11.06	12	0.922	1.54	0.108	0.048
	Greenhouse-Geisser	11.06	9.269	1.193	1.54	0.131	0.048
	Huynh-Feldt	11.06	12	0.922	1.54	0.108	0.048
	Lower-bound	11.06	2	5.53	1.54	0.223	0.048
Error(Scenario_Trust)	Sphericity Assumed	219.02	366	0.598			
	Greenhouse-Geisser	219.02	282.71	0.775			
	Huynh-Feldt	219.02	366	0.598			
	Lower-bound	219.02	61	3.59			

The Tests of Between-Subjects Effects table indicates that eHMI significantly influences Trust (sig. = .006).
Rule Compliance does not significantly influence Trust (sig. = .099).
Comfortability in sharing the roads with AVs significantly influences Trust (sig. = .002).
The frequency of cycling significantly influences Trust (sig. = .015).

Table 37*: Tests of Between-Subjects Effects - Trust vs eHMI trust enhancement vs Rule Compliance of AVs vs Frequency of cycling*

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	425.528	1	425.528	239.597	0.000	0.797
eHMI	28.451	4	7.113	4.005	0.006	0.208
Rulecompliance	14.521	4	3.630	2.044	0.099	0.118
Comfortability	34.894	4	8.723	4.912	0.002	0.244
Frequency_Rev	15.865	2	7.933	4.466	0.015	0.128
Error	108.337	61	1.776			

Perceived Safety × eHMI trust enhancement × Rule Compliance of AVs × Frequency of cycling

Since the sphericity hypothesis was invalidated (sig. < .001) according to Mauchly's test below, the Greenhouse-Geisser metric is taken into account (*see Tests of Within-Subjects Effects below*).

***Table 38**: Mauchly's Test of Sphericity - Perceived Safety × eHMI trust enhancement × Rule Compliance of AVs × Frequency of cycling*

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Scenario_Safety	0.424	50.398	20	< .001	0.795	1.000	0.167

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + eHMI + Rulecompliance + Comfortability + Frequency_Rev

Within Subjects Design: Scenario_Safety

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

The Tests of Within-Subjects Effects table indicates that the scenario does not significantly interact with Perceived Safety (sig. = 0.173)

The same is true for the interaction of eHMI with Perceived Safety, Rule Compliance with Perceived Safety, Comfortability in sharing the roads with AVs with Perceived Safety and Frequency of cycling with Perceived Safety since their p-values are insignificant (sig. > .05).

Table 39*: Tests of Within-Subjects Effects - Perceived Safety × eHMI trust enhancement × Rule Compliance of AVs × Comfortability in sharing the roads with AVs × Frequency of cycling*

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Scenario_Safety	Sphericity Assumed	6.379	6	1.063	1.57	0.156	0.025
	Greenhouse-Geisser	6.379	4.77	1.337	1.57	0.173	0.025
	Huynh-Feldt	6.379	6	1.063	1.57	0.156	0.025
	Lower-bound	6.379	1	6.379	1.57	0.216	0.025
Scenario_Safety * eHMI	Sphericity Assumed	12.478	24	0.52	0.77	0.780	0.048
	Greenhouse-Geisser	12.478	19.082	0.654	0.77	0.748	0.048
	Huynh-Feldt	12.478	24	0.52	0.77	0.780	0.048
	Lower-bound	12.478	4	3.119	0.77	0.552	0.048
Scenario_Safety * Rulecompliance	Sphericity Assumed	23.091	24	0.962	1.42	0.094	0.085
	Greenhouse-Geisser	23.091	19.082	1.21	1.42	0.117	0.085
	Huynh-Feldt	23.091	24	0.962	1.42	0.094	0.085
	Lower-bound	23.091	4	5.773	1.42	0.239	0.085
Scenario_Safety * Comfortability	Sphericity Assumed	20.711	24	0.863	1.27	0.179	0.077
	Greenhouse-Geisser	20.711	19.082	1.085	1.27	0.201	0.077
	Huynh-Feldt	20.711	24	0.863	1.27	0.179	0.077
	Lower-bound	20.711	4	5.178	1.27	0.291	0.077

Scenario_Safety * Frequency_Rev	Sphericity Assumed	8.712	12	0.726	1.07	0.385	0.034
	Greenhouse-Geisser	8.712	9.541	0.913	1.07	0.386	0.034
	Huynh-Feldt	8.712	12	0.726	1.07	0.385	0.034
	Lower-bound	8.712	2	4.356	1.07	0.350	0.034
Error(Scenario_Safety)	Sphericity Assumed	248.51	366	0.679			
	Greenhouse-Geisser	248.51	291	0.854			
	Huynh-Feldt	248.51	366	0.679			
	Lower-bound	248.51	61	4.074			

The Tests of Between-Subjects Effects table shows that all factors under examination – eHMI, Rule Compliance, Comfortability in sharing the roads with AVs and Frequency of cycling significantly affect Perceived Safety since their significance values are less than .05.

***Table 40**: Tests of Between-Subjects Effects - Perceived Safety × eHMI trust enhancement × Rule compliance of AVs × Comfortability in sharing the roads with AVs × Frequency of cycling*

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	422.690	1	422.690	311.942	0.000	0.836
eHMI	33.777	4	8.444	6.232	0.000	0.290
Rulecompliance	17.926	4	4.482	3.307	0.016	0.178
Comfortability	31.890	4	7.972	5.884	0.000	0.278
Frequency_Rev	13.372	2	6.686	4.934	0.010	0.139
Error	82.657	61	1.355			

Perceived social behaviour × eHMI trust enhancement × Rule Compliance of AVs × Frequency of cycling

Since the sphericity hypothesis was invalidated (sig. = .013) according to Mauchly's test below, the Greenhouse-Geisser metric is taken into account (*see Tests of Within-Subjects Effects below*).

***Table 41**: Mauchly's Test of Sphericity - Perceived Social Behaviour × eHMI trust enhancement × Rule Compliance of AVs × Frequency of cycling*

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
Scenario_SocialComp	0.536	36.617	20	0.013	0.833	1.000	0.167

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + eHMI + Rulecompliance + Comfortability + Frequency_Rev

Within Subjects Design: Scenario_SocialComp

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

The Tests of Within-Subjects Effects table indicates that the scenario does not significantly interact with Perceived Safety (sig. = .864)

The same is true for the interaction of eHMI with Perceived Safety, Rule Compliance with Perceived Safety, Comfortability in sharing the roads with AVs with Perceived Safety and Frequency of cycling with Perceived Safety since their p-values are insignificant (sig. > .05).

***Table 42**: Tests of Within-Subjects Effects - Perceived Social Behaviour × eHMI trust enhancement × Rule Compliance of AVs × Frequency of cycling*

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Scenario_SocialComp	Sphericity Assumed	1.832	6	0.305	0.38	0.893	0.006
	Greenhouse-Geisser	1.832	5.001	0.366	0.38	0.864	0.006
	Huynh-Feldt	1.832	6	0.305	0.38	0.893	0.006
	Lower-bound	1.832	1	1.832	0.38	0.541	0.006
Scenario_SocialComp * eHMI	Sphericity Assumed	17.435	24	0.726	0.9	0.605	0.056
	Greenhouse-Geisser	17.435	20.003	0.872	0.9	0.590	0.056
	Huynh-Feldt	17.435	24	0.726	0.9	0.605	0.056
	Lower-bound	17.435	4	4.359	0.9	0.471	0.056
Scenario_SocialComp * Rulecompliance	Sphericity Assumed	25.583	24	1.066	1.32	0.147	0.08
	Greenhouse-Geisser	25.583	20.003	1.279	1.32	0.165	0.08
	Huynh-Feldt	25.583	24	1.066	1.32	0.147	0.08
	Lower-bound	25.583	4	6.396	1.32	0.274	0.08
Scenario_SocialComp * Comfortability	Sphericity Assumed	12.246	24	0.51	0.63	0.913	0.04
	Greenhouse-Geisser	12.246	20.003	0.612	0.63	0.889	0.04
	Huynh-Feldt	12.246	24	0.51	0.63	0.913	0.04
	Lower-bound	12.246	4	3.062	0.63	0.642	0.04
Scenario_SocialComp * Frequency_Rev	Sphericity Assumed	11.56	12	0.963	1.19	0.288	0.038
	Greenhouse-Geisser	11.56	10.001	1.156	1.19	0.296	0.038
	Huynh-Feldt	11.56	12	0.963	1.19	0.288	0.038
	Lower-bound	11.56	2	5.78	1.19	0.311	0.038

Error(Scenario_SocialComp)	Sphericity Assumed	296.117	366	0.809			
	Greenhouse-Geisser	296.117	305.04	0.971			
	Huynh-Feldt	296.117	366	0.809			
	Lower-bound	296.117	61	4.854			

The Tests of Between-Subjects Effects table shows that all factors under examination – eHMI, Rule Compliance and Comfortability in sharing the roads with AVs significantly affect Perceived Social Behaviour.
The Frequency of cycling does significantly affect Perceived Social Behaviour since its significance value is greater than .05.

***Table 43**: Tests of Between-Subjects Effects - Perceived Social Behaviour × Gender × Experience*

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	477.796	1	477.796	287.873	0.000	0.825
eHMI	25.001	4	6.250	3.766	0.008	0.198
Rulecompliance	19.629	4	4.907	2.957	0.027	0.162
Comfortability	25.033	4	6.258	3.771	0.008	0.198
Frequency_Rev	9.640	2	4.820	2.904	0.062	0.087
Error	101.244	61	1.660			

E. Multinomial logistic regression for cyclists' intended reaction per scenario

It has already been mentioned that there is a need to reclassify the Reaction of cyclists to provide for a better distribution of the responses before proceeding with MNLR.

This new classification is now given to all Sc_j_Re_Rev variable(s)
(where j=1,7 is the scenario number).

Now, since the Reaction variable is categorical by design and all other variables are either categorical or ordinal, the Multinomial Logistic Regression technique is applied.

The assumptions for the test have already been mentioned in Chapter 4.3.3.

The dependent variable is the scenario reaction (Sc_j_ Re_Rev),

The independent variables are:

- The familiarity with AVs (Familiarity),
- Age group (AgeGroup_Rev),
- Experience with AVs (Experience_Rev),
- Participants' responses regarding Trust, Perceived Safety and Perceived Social Behaviour (Sc_j_trust, Sc_j_safety, Sc_j_social_comp, j=1,7 the scenario number).

Therefore, seven (7) independent Multinomial Logistic Regression tests were performed to assess how well the model fits.

The results are presented in the following pages along with a brief explanation of the findings.

Scenario 1: Deceleration at unsignalised intersection (clear deceleration, clear indication of intention)

***Table 44**: Goodness-of-Fit for Scenario 1*

	Chi-Square	df	Sig.
Pearson	73.441	104	.990
Deviance	61.074	104	1.000

Goodness of Fit indicated a very good fit p-value (sig. = 1.000) indicating that the model fits the data well (p-value > .05).

The Model Fitting Information output reinforces the notion that the variables statistically significantly improve the model (as compared with the intercept only) (sig. < .0001).

***Table 45**: Model Fitting Information for Scenario 1*

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	148.487			
Final	61.074	87.413	42	.000

Likelihood Ratio Tests reveal that Age Group Revised (sig = .006), Sc_1_trust (.033) and Sc_1_safety (sig = .021), have a significant effect on predicting the outcome.

***Table 46**: Likelihood Ratio Tests for Scenario 1*

Effect	Model Fitting Criteria -2 Log Likelihood of Reduced Model	Likelihood Ratio Tests Chi-Square	df	Sig.
Intercept	61.074[a]	.000	0	.
Familiarity	67.961	6.887	8	.549
Age Group Revised	79.240	18.166	6	.006
Exprerience_Rev	66.972	5.898	4	.207
Sc_1_trust	77.806	16.732	8	.033
Sc_1_safety	79.134	18.060	8	.021
Sc_1_social_comp	68.057	6.983	8	.538

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Of notable significance is the influence of Age Group and participants' assessment of Trust, Perceived Safety and Perceived Social Behaviour.

From the table below, it can be inferred that the model fits the data very well. The lowest classification rate is 40.0% for the "Deceleration" estimate, while the overall classification accuracy is 80.3%.

***Table 47**: Classification for Scenario 1*

Observed	Predicted Brake	Deceleration	Continue cycling	Percent Correct
Brake	23	0	4	85.2%
Deceleration	1	4	5	40.0%
Continue cycling	3	2	34	87.2%
Overall Percentage	35.5%	7.9%	56.6%	80.3%

Scenario 2: Deceleration at unsignalised intersection (smooth deceleration, no clear indication of intention)

Goodness of Fit indicated a very good fit p-value (sig. 1.000) indicating that the model fits the data well (p-value >.05).

***Table 48**: Goodness-of-Fit for Scenario 2*

	Chi-Square	df	Sig.
Pearson	14.616	108	1.000
Deviance	13.590	108	1.000

The Model Fitting Information output reinforces the notion that the variables statistically significantly improve the model (as compared with the intercept only) (sig. < .0001).

***Table 49**: Model Fitting Information for Scenario 2*

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	129.804			
Final	14.976	114.827	38	.000

Likelihood Ratio Tests reveal that Age Group Revised, Experience Revised, Sc_2_trust, Sc_2_safety and Sc_2_social_comp all with p-values at (sig < .0001), have a significant effect on predicting the outcome.

***Table 50**: Likelihood Ratio Tests for Scenario 2*

Effect	Model Fitting Criteria -2 Log Likelihood of Reduced Model	Likelihood Ratio Tests Chi-Square	df	Sig.
Intercept	14.976[a]	.000	0	.
Familiarity	72.262	57.286	8	.000
Age Group Revised	51.922	36.945	6	.000
Exprerience_Rev	36.252	21.275	4	.000
Sc_2_trust	51.679	36.703	6	.000
Sc_2_safety	55.174	40.198	6	.000
Sc_2_social_comp	52.705	37.729	8	.000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Of notable significance is the influence of all inputs Familiarity with AVs, Age Group, Experience level and participants' assessment of Trust, Perceived Safety and Perceived Social Behaviour.

From the table below, it can be inferred that the model fits the data very well. The lowest classification rate is 88.2% for the "Continue cycling" estimate while the overall accuracy in classification level is 96.1%.

***Table 51**: Classification for Scenario 2*

Observed	Predicted Brake	Deceleration	Continue cycling	Percent Correct
Brake	49	0	1	98.0%
Deceleration	0	9	0	100.0%
Continue cycling	1	1	15	88.2%
Overall Percentage	65.8%	13.2%	21.1%	96.1%

Scenario 3: Constant speed on a straight road

Goodness of Fit indicated a very good fit p-value (sig. = 1.000) indicating that the model fits the data very well (p-value >.05).

***Table 52**: Goodness-of-Fit for Scenario 3*

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	.192	102	1.000
Deviance	.382	102	1.000

The Model Fitting Information output reinforces the notion that the variables statistically significantly improve the model (as compared with the intercept only) (sig = .023).

***Table 53**: Model Fitting Information for Scenario 3*

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	60.145			
Final	.382	59.763	40	.023

Likelihood Ratio Tests reveal no statistical significance among variables (all p-values >.05).

***Table 54**: Likelihood Ratio Tests for Scenario 3*

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	.382[a]	.000	0	.
Familiarity	3.871[b]	3.489	8	.900
Age Group Revised	7.804[b]	7.422	6	.284
Exprerience_Rev	3.211[b]	2.830	4	.587
Sc_3_trust	.629[b]	.248	6	1.000
Sc_3_safety	2.823[b]	2.441	8	.964
Sc_3_social_comp	.833[b]	.452	6	.998

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.
b. Unexpected singularities in the Hessian matrix are encountered. This indicates that either some predictor variables should be excluded or some categories should be merged.

Of notable significance is that none of the inputs is statistically significant.

From the table below, it can be inferred that the model fits the data perfectly. The classification rate is excellent at 100.0% overall accuracy.

***Table 55**: Classification for Scenario 3*

Classification

Observed	Predicted			
	Brake	Deceleration	Continue cycling	Percent Correct
Brake	6	0	0	100.0%
Deceleration	0	2	0	100.0%
Continue cycling	0	0	68	100.0%
Overall Percentage	7.9%	2.6%	89.5%	100.0%

Scenario 4: Sudden acceleration encounter on a straight road

Goodness of Fit indicated a very good fit p-value (sig. = 1.000) indicating that the model fits the data very well (p-value >.05).

***Table 56**: Goodness-of-Fit for Scenario 4*

	Chi-Square	df	Sig.
Pearson	20.041	106	1.000
Deviance	24.069	106	1.000

The Model Fitting Information output reinforces the notion that the variables statistically significantly improve the model (as compared with the intercept only) (sig. < .0001).

***Table 57**: Model Fitting Information for Scenario 4*

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	108.981			
Final	24.069	84.912	42	.000

Likelihood Ratio Tests reveal Sc_4_safety (sig = .046), has a significant effect on predicting the outcome.

***Table 58**: Likelihood Ratio Tests for Scenario 4*

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	24.069[a]	.000	0	.
Familiarity	33.012	8.943	8	.347
Age Group Revised	33.155	9.086	6	.169
Exprerience_Rev	28.246	4.177	4	.383
Sc_4_trust	32.788	8.719	8	.367
Sc_4_safety	39.794	15.725	8	.046
Sc_4_social_comp	38.199	14.130	8	.078

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Of notable significance is that participants' perception of safety is statistically significant.

From the table below, it can be inferred that the model fits the data very well. The lowest classification rate is 78.9% for the "Brake" estimate while the overall accuracy in classification level is 90.8%.

***Table 59**: Classification for Scenario 4*

	Predicted			
Observed	Brake	Deceleration	Continue cycling	Percent Correct
Brake	15	0	4	78.9%
Deceleration	0	3	0	100.0%
Continue cycling	3	0	51	94.4%
Overall Percentage	23.7%	3.9%	72.4%	90.8%

Scenario 5: Use of external Human-Machine Interface (eHMI) at intersections (cyclist prioritisation)

Goodness of Fit indicated a very good fit p-value (sig. 1.000) indicating that the model fits the data well (p-value >.05).

Table 60*: Goodness-of-Fit for Scenario 5*

	Chi-Square	df	Sig.
Pearson	.123	102	1.000
Deviance	.245	102	1.000

The Model Fitting Information output reinforces the notion that the variables statistically significantly improve the model (as compared with the intercept only) (sig = .001).

Table 61*: Model Fitting Information for Scenario 5*

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	74.352			
Final	1.631	72.721	40	.001

Likelihood Ratio Tests reveal that Age Group Revised (sig < .0001), Experience Revised (sig < .0001) and Sc_5_social_comp (sig < .0001), have a significant effect on predicting the outcome.

***Table 62**: Likelihood Ratio Tests for Scenario 5*

Effect	Model Fitting Criteria -2 Log Likelihood of Reduced Model	Likelihood Ratio Tests Chi-Square	df	Sig.
Intercept	1.631[a]	.000	0	.
Familiarity	13.670[b]	12.039	8	.149
Age Group Revised	50.037[c]	48.406	6	.000
Exprerience_Rev	471.092[b]	469.461	4	.000
Sc_5_trust	13.083[b]	11.453	6	.075
Sc_5_safety	4.177[b]	2.546	8	.960
Sc_5_social_comp	43.442[b]	41.811	6	.000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

b. Unexpected singularities in the Hessian matrix are encountered. This indicates that either some predictor variables should be excluded or some categories should be merged.

c. The log-likelihood value cannot be further increased after maximum number of step-halving.

Of notable significance is that participants' age group, experience level with AVs and perception of social compliance are statistically significant.

From the table below, it can be inferred that the model fits the data very well. The lowest classification rate is 98.5% for the "Continue cycling" estimate while the overall accuracy in classification level is 98.7%.

***Table 63**: Classification for Scenario 5*

Observed	Predicted Brake	Predicted Deceleration	Predicted Continue cycling	Predicted Percent Correct
Brake	8	0	0	100.0%
Deceleration	0	3	0	100.0%
Continue cycling	1	0	64	98.5%
Overall Percentage	11.8%	3.9%	84.2%	98.7%

Scenario 6: Use of external Human-Machine Interface (eHMI) at intersections (no cyclist prioritisation)

Goodness of Fit indicated a very good fit p-value (sig. = 1.000) indicating that the model fits the data very well (p-value >.05).

***Table 64**: Goodness-of-Fit for Scenario 6*

	Chi-Square	df	Sig.
Pearson	.000	104	1.000
Deviance	.000	104	1.000

The Model Fitting Information output reinforces the notion that the variables statistically significantly improve the model (as compared with the intercept only) (sig = .026).

***Table 65**: Model Fitting Information for Scenario 6*

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	61.572			
Final	.000	61.572	42	.026

Likelihood Ratio Tests reveal that Familiarity (sig = .010), Age Group Revised (sig < .0001), Experience Revised (sig < .0001) and Sc_6_safety (sig = .010), have a significant effect on predicting the outcome.

***Table 66**: Likelihood Ratio Tests for Scenario 6*

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	.000[a]	.000	0	.
Familiarity	20.047	20.047	8	.010
Age Group Revised	28.024	28.024	6	.000
Exprerience_Rev	23.524	23.524	4	.000
Sc_6_trust	13.960	13.960	8	.083
Sc_6_safety	20.141	20.141	8	.010
Sc_6_social_comp	5.545[b]	5.545	8	.698

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.
b. Unexpected singularities in the Hessian matrix are encountered. This indicates that either some predictor variables should be excluded or some categories should be merged.

Of notable significance is that participants' familiarity with AVs, age group, experience level with AVs and perception of safety are statistically significant.

From the table below, it can be inferred that the model fits the data perfectly. The classification rate is excellent at 100.0% overall accuracy.

***Table 67**: Classification for Scenario 6*

	Predicted			
Observed	Brake	Deceleration	Continue cycling	Percent Correct
Brake	67	0	0	100.0%
Deceleration	0	1	0	100.0%
Continue cycling	0	0	8	100.0%
Overall Percentage	88.2%	1.3%	10.5%	100.0%

Scenario 7: Cyclist response to AV deceleration

Goodness of Fit indicated a very good fit p-value (sig. = .997) indicating that the model fits the data well (p-value >.05).

***Table 68**: Goodness-of-Fit for Scenario 7*

	Chi-Square	df	Sig.
Pearson	95.067	100	.621
Deviance	65.971	100	.997

The Model Fitting Information output reinforces the notion that the variables statistically significantly improve the model (as compared with the intercept only) (sig = .034).

***Table 69**: Model Fitting Information for Scenario 7*

Model	Model Fitting Criteria -2 Log Likelihood	Likelihood Ratio Tests Chi-Square	df	Sig.
Intercept Only	130.402			
Final	70.130	60.272	42	.034

Likelihood Ratio Tests reveal no statistical significance for any independent variable.

***Table 70**: Likelihood Ratio Tests for Scenario 7*

Effect	Model Fitting Criteria -2 Log Likelihood of Reduced Model	Likelihood Ratio Tests Chi-Square	df	Sig.
Intercept	70.130[a]	.000	0	.
Familiarity	78.323	8.193	8	.415
Age Group Revised	72.573	2.443	6	.875
Exprerience_Rev	72.422	2.292	4	.682
Sc_7_trust	77.251	7.120	8	.524
Sc_7_safety	84.832	14.701	8	.065
Sc_7_social_comp	71.167	1.037	8	.998

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Of notable significance is that none of the inputs is statistically significant.

From the table below, it can be inferred that the model fits the data very well. The lowest classification rate is 42.9% for the "Deceleration" estimate while the overall accuracy in the classification level is 80.3%.

Table 71*: Classification for Scenario 7*

	Predicted			
Observed	Brake	Deceleration	Continue cycling	Percent Correct
Brake	18	0	5	78.3%
Deceleration	1	3	3	42.9%
Continue cycling	5	1	40	87.0%
Overall Percentage	31.6%	5.3%	63.2%	80.3%

General conclusion: *In general, the Multinomial Logistic Regression works well in modelling the respondents' reactions per scenario. The overall accuracy ranges from 80.3% to 100%. It is clear that the model had difficulty spotting deceleration in scenarios 1 and 7 where it struggled with the "brake" and "continue cycling" labelling.*

For the record, the model had accuracy levels of 40% for Scenario 1 and 42.9% for Scenario 7.

F. Scientific Paper

A social driving style of highly automated vehicles from cyclists' perspective

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ABSTRACT

The introduction of Highly Automated Vehicles (HAVs) presents challenges for everyday transport, particularly impacting cyclists, who are part of what is called vulnerable road users. While HAVs promise to optimise traffic flow and enhance safety, concerns about their safety remain. This research addresses the gap in understanding cyclists' expectations and perceptions of social driving behaviour in the Netherlands. By developing a conceptual framework and a questionnaire, the study explores the interactions between cyclists and HAVs, focusing on trust, perceived safety and perceived social behaviour of cyclists in urban settings like The Hague. Findings reveal that cyclists' comfortability with sharing the roads with HAVs and their belief that HAVs are more likely to follow the rules influence their opinions. Additionally, the use of electronic Human-Machine Interface (eHMI) in HAVs, seems to positively affect cyclists' trust, perceived safety and perceived social behaviour. Notably, it is found that demographic factors have little influence on cyclists' attitudes towards HAVs. The study underscores the importance of predictability in fostering higher safety ratings and demonstrates how the characteristics and driving behaviour of HAVs affect cyclist perceptions. These insights can guide policymakers and developers in devising solutions that enhance the safety and well-being of all road users, ensuring the effective integration of HAV technology while minimising potential drawbacks.

1. Introduction

1.1. Background

Automated vehicles (AVs) have been developed over recent years and by 2030 many AV-related technologies are anticipated to become widespread in the majority of new vehicles [1]. Many experts have high expectations over their capabilities, suggesting a possible road safety and traffic flow enhancement could take place since human errors, which are responsible for some 90% of road accidents, are to be reduced [2]. Further, it is argued that AVs can avoid risky behaviours and they are likely to improve real-time route planning [3]. Additionally, this technology has the potential to enhance accessibility for older adults and individuals with disabilities and also to encourage sustainable mobility through shared AV services [5][6][7]. However, part of the public expresses its concerns and perceptions regarding the massive implementation of AVs [8]. Precisely, some experts draw their attention to issues related to fairness in transportation costs, the risk of the AV being hacked or the overlapping responsibilities in case of a traffic accident [9] [10] [11] [12].

In order to limit possible reservations that may exist, it is important to establish effective interactions between Highly Automated Vehicles (HAVs) and other road users, such as cyclists. Hence, the concept of socially compliant behaviour from the HAVs' side is crucial in this instance. According to Schwarting et al., socially compliant driving is defined as predictable behaviour in interactions with humans and autonomous agents [13]. Considering that AV technology includes high levels of automation, which in turn may partially or fully replace human driving, a communication void between cyclists and HAVs is likely to arise [14]. Cyclists being vulnerable road users (VRUs) are susceptible to being severely injured in case of an accident with another vehicle, as they lack physical protection [8].

Cycling culture in countries is also another important factor that may affect cyclist-HAV interactions. As per the findings of Li et al. [15], it has been found that cyclist injuries have risen in areas with poor integration between cyclists and vehicles. Consequently, Imanishimwe and Kumar [16] stress the need to understand the impact of HAVs on road safety and VRU well-being, given concerns about HAV-related traffic accidents and fatalities.

1.2. Research problem

Social driving is crucial for the successful integration of HAV technology. As mentioned in Section 1.1., socially compliant driving of HAVs can be defined as showing predictability in their interactions with other traffic participants, while Vinkhuyzen and Cefkin [17] describe it as the behaviour of HAV in specific traffic interactions.

Several factors that are related to either cyclists or HAV characteristics can influence social compliance. However, little attention has been given to how these factors interact in the context of HAVs sharing the road with cyclists, who are VRUs lacking physical protection. Therefore, it is essential to explore which factors are actively involved in the cyclist-HAV interaction and how these factors are interrelated.

Specifically, regarding the HAVs, it was decided to examine those that are considered highly automated (i.e., having levels of automation 4 and 5). Vlakveld et al. [18] highlight a gap in research focusing on cyclists' viewpoints, particularly in experimental research. This gap prevents a full understanding of the factors influencing interactions between cyclists and HAVs, particularly the social compliance of HAV components. Thus, the current research aims to capture cyclists' perceptions and expectations of HAVs.

1.3. Research gap, objective and questions

Achieving social compliance with AVs constitutes a major challenge, requiring a thorough understanding of all relevant factors involved. This literature review focuses on two traffic agents: cyclists and AVs. The study aims to address the following main research question:

- ➢ *What factors do cyclists consider important for the socially compliant driving behaviour of HAVs?*

To support this research question, four sub-questions have been formulated:

- *What are the conceptual determinants of socially compliant driving behaviour?*
- *Under which conditions do cyclists perceive an HAV to drive in a social manner?*
- *Which factors influence cyclists' perceptions and expectations of HAVs regarding Trust, Perceived Safety and Perceived Social Behaviour?*
- *Do Trust, Perceived Safety and Perceived Social Behaviour affect cyclists' intended behaviour? If so, what other factors might also influence this intended behaviour?*

These sub-questions provide a structured approach since they explore different aspects of the topic. By addressing these questions will provide a clearer understanding of cyclists' expectations and perceptions regarding socially compliant HAV driving behaviour. This knowledge will help manufacturers and policymakers create HAVs that make interactions with cyclists safer.

2. Literature review

The primary aim of this literature review is to investigate different viewpoints and comprehensively address the knowledge gap identified earlier. This is achieved through a critical review approach, analysing research findings relevant to the topics of this study. These topics are structured into two main pillars: a) the role of cyclists as VRUs and b) the concept of social compliance in HAV driving. Each of these pillars is further divided into specific subtopics, enhancing the thoroughness and scope of the analysis.

2.1. Cyclists as vulnerable road users

Cycling is a major urban transport mode involving non-motorised two-wheel travel [8]. Cyclists, classified as VRUs along with pedestrians, travel with minimal protection compared to AV or human-driven vehicle occupants. Research indicates cyclists exhibit distinct eye-gazing behaviours, focusing more on the road ahead and performing fewer shoulder checks [1].

Cyclists' navigation into urban settings is a significant challenge for HAVs, due to cyclists' unpredicted behaviour [19]. A proposed solution for overcoming this obstacle is the use of a Human-Machine-Interface by AVs to inform both other VRUs or vehicles, while another suggested strategy is the use of External-Machine-Human-Interface (eHMI) by HAVs to signal cues through lights or displays [20].

2.1.1. Cyclists' perceptions of automated vehicles

Positive perceptions of AV behaviour influence acceptance of narrower gaps and shorter headways [21]. Addressing VRUs' concerns and perceptions is essential for successful AV integration. Perceived safety involves users' subjective risk assessments, influencing behaviours such as increased vigilance [22].

Berge et al. [19] conducted a study examining cyclists' perceptions of AVs. Cyclists foresee ongoing traffic uncertainties with respect to AVs in the future, suggesting AV algorithms should integrate human biases and attitudes. In the same research, it was also found that cyclists prefer AVs to mimic human behaviours and respond to sudden movements, suggesting that safety is of paramount importance to them.

Cyclists perceive cycling near AVs as less safe compared to walking or driving near self-driving vehicles [23]. Moreover, perceived safety is influenced by technology awareness, socio-demographic factors and national contexts [24]. VRUs' safety perceptions are shaped by exposure to AVs and by people's interest in AV-related news [25] [26].

2.1.2. Cyclists' acceptance & trust of highly automated vehicles

Recent studies have explored how cyclists perceive AVs and their interactive experiences. According to Xing et al. [27], public opinions on AVs may change over time as familiarity with the technology increases. Further, Li et al. [15] investigated demographic impacts on cyclists' readiness to share roads with Fully Autonomous Vehicles (FAVs). Their findings reveal that older individuals and male cyclists generally show less willingness to coexist with FAVs compared to younger counterparts, mentioning concerns about attitude, trust, system effectiveness and compatibility.

Moreover, Xing et al. [27] examined VRUs' interactions with AVs through surveys in Pittsburgh from 2017 to 2019. They found that direct experiences with AVs positively influenced VRUs' receptivity and perceptions, although overall receptivity levels in Pittsburgh did not see significant shifts with AV introduction.

User acceptance is crucial for AVs. Nordhoff et al. [24] stress the importance of safe interactions between AVs and Vulnerable Road Users (VRUs) for effective AV deployment. Questionnaire studies provide valuable insights into public AV acceptance, yet Nordhoff et al. [28] caution they often offer surface-level insights.

Lee & See [29] define trust as including attitudes, intentions and behaviours, involving one party's willingness to entrust tasks to another with the expectation of positive outcomes [22]. In automation, trust reflects users' readiness to rely on automated systems [30]. Papadimitriou et al. [2] defined trust as an expectation that an automated agent will help an individual achieve their goals in unpredictable and vulnerable situations. Trust levels are influenced by contextual factors like task complexity and perceived risks [31]. Higher trust in autonomous driving correlates with user experience and can vary due to individual characteristics, external factors and system performance [22]. However, excessive reliance on automation may lead to misuse and reduced vigilance, affecting monitoring performance [32].

2.1.3. Expectations and interaction of cyclists with automated vehicles

In mixed traffic settings, interactions between cyclists and AVs, especially at unsignalised intersections, are complex and critical for traffic safety [34]. Vissers et al. [35] emphasise the challenge of establishing standard interaction protocols for AVs due to varying cyclist behaviours. Effective communication between VRUs and AVs is essential, with AVs reacting appropriately when aware of VRUs' intentions and VRUs responding positively to AVs' actions [36]. Studies indicate that cyclists tend to exhibit rational responses when interacting with machines [37].

Nordhoff et al. [28] conducted an interview on public expectations of autonomous shuttles, revealing high expectations for obstacle avoidance and route navigation, which was also accompanied by disappointment over speed limitations and the presence of onboard staff. Media portrayals of AV capabilities influence public perceptions and behaviours based on previous experiences and traffic regulations [35].

Vlakveld et al. [18] conducted an experiment to capture cyclists' intentions and found that cyclists might yield to cars when they have priority, especially when approaching AVs. Furthermore, in the same study, it was also mentioned that communication from AVs has a considerable impact on cyclists' willingness to yield, primarily when it indicates awareness and adherence to traffic rules. Madigan et al. [37] suggest that VRUs seek greater separation from AV paths.

Recent studies highlight drivers' willingness to accept gaps in front of AVs, affecting merging behaviour at intersections. Factors such as AV appearance, driving style and driver demographics influence gap acceptance behaviours [21][33].

Therefore, understanding these behavioural adjustments is crucial for traffic efficiency and safety, especially in complex scenarios like left turns. Also, implementing infrastructure-to-vehicle (I2V) communication systems could enhance AV integration [33].

2.2. Social compliance of automated vehicles

In road environments, interactions among pedestrians, cyclists and drivers involve communication, coordination and occasional competition [3]. Markkula et al. [38] explain that these interactions occur when the behaviours of multiple users are influenced by the possibility of sharing the same space simultaneously. This dynamic is evident when AVs are integrated into mixed traffic settings, where initial concerns highlighted by media reports include potential aggression or harassment towards AVs [3].

2.2.1. Driving style of automated vehicles

Driving styles in AVs include a range of behaviours that significantly influence acceptance, trust and takeover behaviours [39]. These driving styles represent automated skills and consistent behaviours across various driving scenarios. However, there is ongoing debate on how to conceptualise and measure driving styles [40], which typically reflect individual preferences and habits related to speed, overtaking decisions and stable driving characteristics. Key indicators include speed, acceleration, time headway, steering, gap acceptance and adherence to traffic rules [41].

According to Ma & Zhang [39], defensive driving styles prioritise safety with lower speeds, smooth acceleration, early deceleration and wider following distances, while aggressive styles favour higher speeds, tailgating, abrupt manoeuvres, high beam usage and honking.

Furthermore, the Social Value Orientation (SVO), derived from social psychology, quantifies how individuals balance personal rewards against rewards for others [42]. This metric can be used to define the driving style to which an AV lies and captures tendencies towards social preferences like altruism, fairness, reciprocity, inequity aversion and egalitarianism [13]. AVs can anticipate behaviours by understanding others' SVO, informing decisions like yielding during interactions [13].

It is worth mentioning, that anthropomorphism in AVs tends to boost people's trust due to perceived social presence, safety, intelligence and trustworthiness [43].

Driving styles significantly influence trust in AVs [31]. There are instances where varying AV styles can lead to inconsistent behaviour that contradicts the expectations of other road users, in combination with the absence of universally accepted ethical and safety standards for machines [44]. Alignment between an individual's driving style and that of AVs enhances trust in AV systems [39]. Confidence in AV technology is associated with maintaining a central lane position [45]. Defensive driving styles generally receive higher trust compared to aggressive styles due to their predictability [31].

2.2.2. Communicating intentions of automated vehicles

Cyclists' perceptions of AVs are significantly shaped by how effectively these vehicles communicate in real-world traffic. Berge et al. [20] categorised communication methods into visual, auditory, motion-based and wireless. Cyclists often encounter obstacles such as parked cars and sudden stops in bike lanes due to unpredictable actions by other road users [19]. Therefore, a key challenge for AVs is clearly conveying their driving intentions to others [46].

There is debate among researchers about the best communication approach. Harkin et al. [47] discuss that experts express differing views, with some supporting explicit methods, while others preferring implicit approaches. Implicit communication, as defined by Markkula et al. [38], involves behaviours that affect a user's movement or perception and may signal something to others, even if they are unaware [48]. Explicit communication, on the other hand, involves actions like hand gestures or headlight flashes that demand a response [38][48]. According to Berge et al. [19], cyclists desire reliable detection and prefer AVs to use explicit communication.

Interactions between human drivers and AVs in mixed traffic present challenges, as AVs strictly adhere to regulations like speed limits and may not understand unwritten social norms [49][50]. Effective communication of AV intentions is crucial for safe interactions with human road users. It is vital to develop clear methods for AVs to communicate their actions, whether stopping, moving, or preparing for manoeuvres, as AV technology advances [17].

External human-machine interfaces (eHMIs) play a crucial role in facilitating these interactions. Schieben et al. [51] categorise eHMIs into:

1. ***Driving Status Information***: Updates on the AV's automation status and operational mode.
2. ***Future Manoeuvre Information***: Insights into upcoming AV actions to help others anticipate movements.
3. ***Environment Perception***: Indicates if the AV has detected nearby road users, ensuring awareness.
4. ***Cooperation Capabilities***: Evaluate how well the AV interacts with others in different traffic scenarios, demonstrating its ability to collaborate effectively.

Despite eHMI's potential to facilitate safe interactions between AVs and other road users, concerns about misunderstandings must be addressed [52].

Cefkin et al. [53] initiated research into interactions with HAVs and their impact on traffic dynamics. AVs present distinct kinematic cues, thus creating challenges in micro-interactions. To address this, the "Intention Indicator" was introduced as a novel communication signal to clearly convey an AV's operational state. Visible from all angles, this signal aims to enhance road safety and understanding. Simulation studies at intersections with multiple AVs revealed that widespread adoption of the "Intention Indicator" could improve traffic flow, especially with user familiarity. Recommendations include using simple symbols, discrete signal states, international colour standards and ensuring visibility at eye level [53].

De Winter and Dodou [14] discuss the "social interaction void" created by automated driving due to the absence of human drivers, advocating for eHMIs to facilitate pedestrian communication. Human factors experts caution against overly instructive eHMIs to prevent accidents and misunderstandings [54], while others favour text-based eHMIs for direct communication. Berge et al. [19] explored AV-cyclist interactions and demonstrated cyclists' preference for explicit recognition and communication from AVs, especially with HMIs improving interaction and providing location information.

Despite numerous eHMI proposals, comprehensive evaluations remain limited. Proposed concepts like green and red front brake lights have been suggested, with green indicating safe crossing and red signalling AV's inability to proceed, favouring a pedestrian's perspective. Pedestrians generally favour egocentric views, tending to cross in front of green eHMIs [55].

On-bike HMIs offer another approach to enhancing AV-cyclist interactions, as examined by Berge et al. [19]. Cyclists show interest in these interfaces, particularly for features displaying information about other road users' positions and promoting overall communication. However, adoption concerns remain, including doubts about practical utility and ethical implications, such as potential shifts in safety responsibilities to VRUs.

2.2.3. Behavioural adaptation of automated vehicles

Behavioural adaptation in automated driving is defined by Rudin-Brown & Jamson [56] as changes in driver or traveller behaviour following interactions with modifications to the road traffic system, both deliberate and unintended. Understanding these adaptations is crucial for how individuals interact with AVs on the road. The adoption of AVs has prompted mixed reactions. Schwarting et al. [13] argue that AVs often exhibit cautious driving behaviours, potentially causing traffic congestion and misunderstandings, particularly at intersections and during left turns. This caution increases vulnerability to human aggression and reduces clarity in intentions, contributing to AV-related accidents. Some experts question whether current assumptions about human and AV behaviours accurately predict improvements in driving safety [3]. Given public unfamiliarity with AV technology, understanding AV operations is challenging, hence more research and development are needed to meet public expectations.

2.3. Main findings

This literature review examines two major topics: cyclists as vulnerable road users and the factors related to social compliance in Highly Automated Vehicles (HAVs). Cyclists lack protection compared to vehicle occupants, a thing which is crucial for urban mobility and favours HAVs that display human-like behaviours for safety. However, trust issues persist in mixed-traffic settings. Receptivity, user acceptance and trust are important in shaping cyclists' attitudes towards HAVs, evolving with familiarity over time and influenced by socio-demographic factors.

In mixed-traffic environments, especially at intersections, the interactions between cyclists and

HAVs are complex, with individual differences hindering standardised protocols. Effective communication is crucial for safe interactions, meaning that clear channels between HAVs and cyclists need to exist to interpret their intentions. HAV driving styles significantly impact acceptance and trust, with defensive styles favouring safety and predictability.

External Human-Machine Interfaces (eHMIs) play a vital role in conveying driving status and future manoeuvres, thus enhancing predictability and safety. However, debates persist over eHMI design principles, particularly instructive versus explicit communication. Innovations like the "Intention Indicator" aim to improve predictability at intersections, addressing concerns over eHMI practicality and ethical implications.

As HAV technology advances, research focuses on integrating HAVs into mixed traffic, exploring behavioural adaptation, driving styles and HAV intent communication, a thing which is essential for trust and social compliance.

3. Methodological Approach

3.1. Research and survey design

A conceptual framework was developed through a literature review and interviews with three professors and one PhD student from Delft University of Technology, selected for their expertise in cyclist-HAV interactions. They provided insights on cyclist behaviour, definitions of socially compliant HAV behaviour, recommended studies and identified critical factors influencing cyclists' perceptions. Their feedback refined the initial framework, ensuring the completeness and accuracy of relationships. Subsequently, a survey based on this framework was designed to explore how HAV dynamics, demographics, cycling frequency and familiarity with HAVs influence cyclists' trust, perceived safety and perceived social behaviour regarding self-driving vehicles.

3.2. Participants recruitment

The survey aimed to recruit individuals aged 18 and above residing in the Netherlands, with a target of at least 50 participants. Convenience sampling was utilised, reaching out to acquaintances, friends, lecturers and fellow students via WhatsApp groups and cycling associations. The survey was hosted on Microsoft Forms and SurveyCircle, an online platform for student surveys. Ultimately, 76 participants who met the criteria were successfully recruited, achieving the desired sample size for the study.

3.3. Data collection and analysis

The survey was approved by the Human Research Ethics Committee of Delft University of Technology in March 2024 (reference no. 3888) and was conducted from March 13th to April 3rd, 2024. Participants were assured of confidentiality and voluntary participation rights.

The main research question, addressed in Section 1.3, is: "*What factors do cyclists consider important for socially compliant driving behaviour with respect to HAVs?*" This question is explored through four sub-questions.

Sub-question 1 examines the conceptual determinants of socially compliant driving behaviour, derived from a literature review and expert interviews with professors from Delft University of Technology. The resulting conceptual framework is detailed in Section 4.1.

Sub-question 2 investigates the conditions under which cyclists perceive HAVs as driving in a socially compliant manner, analysed descriptively using data from the online survey. Section 4.2 provides the analytical approach.

Sub-question 3 focuses on the factors influencing cyclists' perceptions of HAVs regarding Trust, Perceived Safety and Perceived Social Behaviour. Initial bivariate correlation tests for each dependent variable are followed by Repeated Measures One-Way Analysis of Variance (ANOVA) for detailed exploration, outlined in Section 4.3.

Sub-question 4 assesses whether Trust, Perceived Safety and Perceived Social Behaviour influence cyclists' intended behaviour using Multinomial Logistic Regression. This statistical approach also identifies additional factors affecting cyclists' reactions, detailed also in Section 4.3.

3.4. Traffic scenarios selection and design

The survey focuses on interactions between cyclists and HAVs in urban settings, particularly at unsignalised intersections with shared or non-dedicated bicycle lanes. Berge et al. [19] highlight cyclists' preference for segregated infrastructure like dedicated bike paths and their comfort with signalised intersections due to clearer traffic guidance. Thus, studying unsignalised intersections is crucial given their frequent traffic conflicts in mixed HAV-cyclist environments.

Furthermore, many bike-vehicle incidents occur when vehicles approach cyclists perpendicularly [1]. Scenarios were carefully designed to vary HAV dynamics (speed, direction), intention clarity (eHMI indication or not) and HAV speed changes (constant, decelerating, accelerating, braking). This variation allows a comprehensive exploration of factors influencing cyclists' perceptions and responses to HAV interactions in diverse urban settings.

The survey aims to analyse cyclists' trust, perceived safety, perceived social behaviour of HAVs and cyclists' reactions as dependent variables across different traffic scenarios. Independent variables include HAV driving dynamics, intention clarity, demographics (gender, age, education), cycling frequency and familiarity with HAVs.

The survey was structured into four sections:

1. Demographic questions were presented in a multiple-choice format.
2. Participants were asked about their familiarity with the concept of socially compliant driving of HAVs and then invited to give open-ended responses about actions contributing to it. Definitions of socially compliant driving were provided after they gave their responses.
3. Eight Likert scale statements gauged agreement (1 to 5) on propositions regarding cyclists' views of HAVs.
4. Seven scenarios assessed Trust, Perceived Safety and Perceived Social Behaviour towards HAVs, with responses rated on a 1-5 Likert scale alongside indications of their reactions.

Scenario descriptions included a map with the exact location of the site. An indicative example of how they were presented is as follows:

The survey scenarios and their objectives are summarised below:

- ***Scenario 1***: Cyclists imagined approaching an intersection while an HAV, clearly signalling its intent to decelerate and yield priority to cyclists. This scenario assessed the impact of clear HAV intentions.
- ***Scenario 2***: Similar to Scenario 1, but the HAV decelerated without clear signalling. This scenario explored the effect of ambiguous HAV intentions.
- ***Scenario 3***: Cyclists imagined riding along a street with an HAV maintaining a constant speed alongside them. This scenario examined perceptions of consistent HAV behaviour.
- ***Scenario 4***: Similar to Scenario 3, but the HAV suddenly accelerated. This scenario assessed reactions to unexpected HAV behaviour.
- ***Scenario 5***: At an intersection, an HAV equipped with an eHMI signalled it would yield the cyclist to pass. This scenario evaluated eHMI's effectiveness in communication.
- ***Scenario 6***: Similar to Scenario 5, but the AV signalled it would proceed through the intersection without yielding. This scenario explored perceptions of eHMI when HAVs do not prioritise cyclists.
- ***Scenario 7***: Cyclists imagined navigating at an intersection while an HAV decelerated to turn left. This scenario captured cyclist reactions to HAV manoeuvres.

4. Results

4.1. Conceptual determinants of socially compliant driving

Following discussions with experts and a literature review, a conceptual framework was developed, as depicted in the figure below. The framework is divided into two parts: the left side focuses on HAV functions and characteristics, while the right side pertains to cyclists. Arrows indicate influence and interaction between elements.

The primary determinant within the HAV segment is driving style, which includes driving dynamics (smooth/sharp acceleration/deceleration, defensive/aggressive driving style) and communication of intentions. These elements are interdependent, as indicated by a bidirectional arrow.

Driving style impacts cyclists' Trust, Perceived Safety and Perceived Social Behaviour regarding HAVs. These three variables are interconnected, as supported by literature and expert interviews. Additional factors, such as demographics, cycling frequency, familiarity with HAVs and cycling infrastructure (e.g., shared roadways or separated lanes), also influence trust. Trust, in turn, affects the perceived safety and perceived social behaviour of HAVs.

Trust, Perceived Safety and Perceived Social Behaviour collectively influence cyclists' responses to HAV interactions. Cyclists' intended behaviour may also reciprocally affect Trust, Perceived Safety and Perceived Social Behaviour and can influence HAV driving style, creating a feedback loop. While some experts question this feedback loop between machines and humans, it is argued that AV sensors facilitate this interaction.

4.2. Descriptive analysis

As noted in Section 3.2, the survey gathered responses from 76 participants, primarily younger individuals, with over 60% under 34 years old. This age distribution reflects those in peak working and commuting years, influencing their views on urban mobility and Highly Automated Vehicles (HAVs). Minimal representation from older age groups was noted.

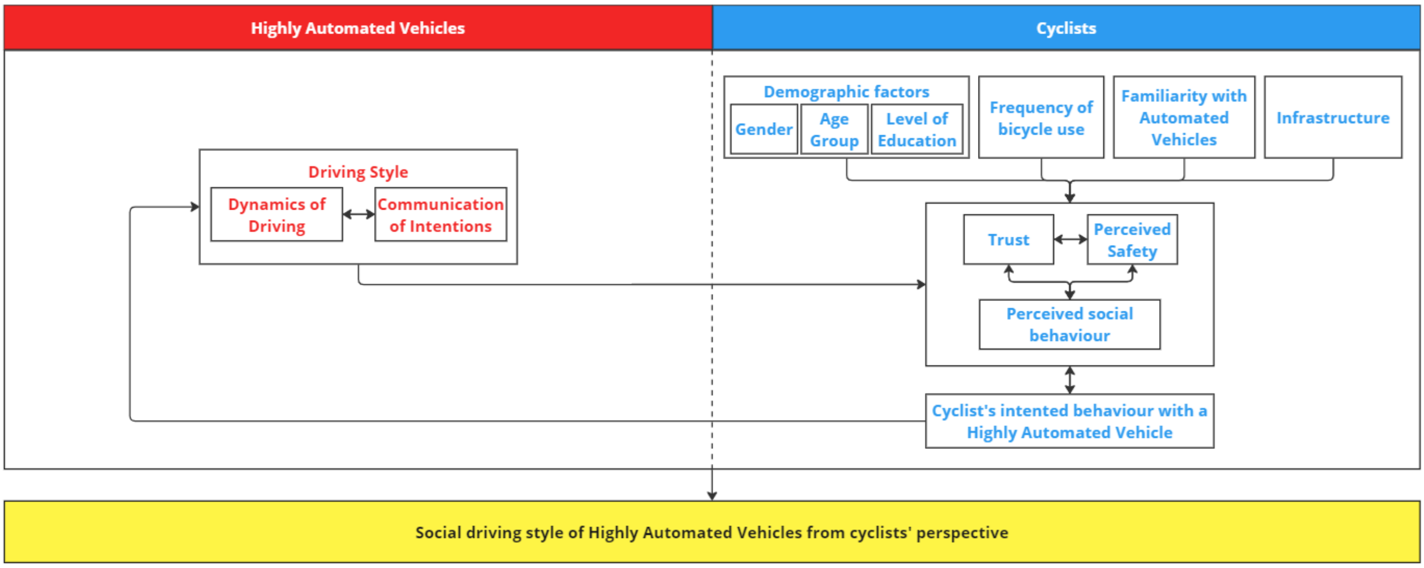
Cycling frequency varied widely among participants. About 37% cycled daily, indicating a preference for active transportation, while 26% cycled several times per week. Nearly 37% cycled less than once a week or never, reflecting diverse cycling habits.

Exposure to Automated Vehicles (AVs) of any level also varied. A notable 44.8% had some familiarity or direct experience with AVs, 27.6% had no engagement and 27.6% had partial familiarity.

The educational profile was predominantly well-educated, with most holding Bachelor's and Master's degrees. There were no respondents with high-school diplomas and only a few had technical/vocational training, indicating a bias towards higher education levels. The high number of Doctoral degree holders suggests engagement with complex subjects, possibly limiting generalisability.

Familiarity with socially compliant driving varied, with 29% being unfamiliar and 42% moderately to highly familiar.

An open-ended question revealed key opinions on HAV behaviours for socially compliant driving. Respondents emphasised rule compliance, predictable driving, safety



and consideration for vulnerable road users, such as yielding to cyclists and consistent behaviour. Ethical considerations and sensory systems for detecting cyclists and pedestrians were also frequently mentioned.

Eight statements were evaluated, revealing varied attitudes and perceptions among respondents:

- Trust in HAVs prioritising cyclist safety showed a balance of positive and negative responses, indicating uncertainty.
- Perceptions of HAVs' communication of intentions followed a similar trend.
- Confidence in predicting HAV behaviour was more positive, with most respondents expressing confidence.
- Comfort in sharing the road with HAVs was evenly distributed, slightly skewed towards positive.
- Use of eHMI by HAVs received predominantly positive responses, indicating enhanced trust.
- Statements on HAVs' possibility of being more rule compliant, predictability being an important element in socially compliant driving of HAVs and people's comfortability in sharing the road with HAVs driving predictably received overwhelming support.

Participants were presented with scenario-based questions to gauge their anticipated responses when encountering HAVs at different locations in The Hague. Detailed descriptions for each scenario can be found in Section 3.4.

The responses indicated that the clarity of the HAV's intentions significantly impacts Trust, Perceived Safety and Perceived Social Behaviour. In cases where the HAV explicitly signalled its intention to pass in front, resulted in higher confidence among cyclists. Conversely, when the HAV did not convey its intentions clearly, it received the lowest ratings.

HAVs equipped with an external Human-Machine Interface (eHMI) showed higher ratings for Trust, Perceived Safety and Perceived Social Behaviour. This suggests that eHMI positively influences perceptions by bridging the communication gap. This aligns with the 73.6% of respondents who viewed eHMI positively in enhancing their trust in HAV intentions.

When the HAV moved alongside the cyclist at a constant speed, positively influenced the cyclist's perceptions due to its predictability. Conversely, a sudden acceleration negatively impacted the cyclist's perceptions. The HAV's driving dynamics, such as deceleration or braking positively influenced participants' views.

4.3. Statistical analysis

To analyse the factors influencing cyclists' perceptions and expectations, a bivariate analysis was conducted to identify strong correlations for each dependent variable (Trust, Perceived Safety and Perceived Social Behaviour). The analysis revealed that cyclists' comfortability in sharing the road with HAVs, the use of eHMIs and HAVs' rule compliance were strongly correlated with the dependent variables. Subsequently, the implementation of Repeated Measures One-Way ANOVA statistical tests confirmed that HAVs equipped with eHMI significantly affect Trust, Perceived Safety and Perceived Social Behaviour. Furthermore, it was found that individuals' comfortability in sharing roads with HAVs and the frequency of their cycling also influence these perceptions. Notably, rule compliance was shown to have a more significant impact on Perceived Safety and Perceived Social Behaviour than the various scenario variations.

To determine whether cyclists' intended reactions could be modelled by incorporating Trust, Perceived Safety and Perceived Social Behaviour, a Multinomial Logistic Regression statistical test was employed. The analysis revealed that Trust, Perceived Safety and Perceived Social Behaviour were indeed influential factors and be included in the model. Additionally, the age group of the individual, their familiarity with the concept of socially compliant driving and their experience with HAVs were significant in modelling the expected cyclist reaction to the situation.

5. Discussion, limitations and recommendations

5.1. Discussion

The survey, developed based on existing literature and expert input, aimed to explore cyclists' perceptions and expectations of interactions with HAVs. Findings indicated that cyclists' trust in HAVs varied significantly depending on how explicitly the HAVs communicated their intentions. For instance, scenarios, where HAVs explicitly decelerated or used an external Human-Machine Interface (eHMI) to signal intentions, received higher trust ratings compared to scenarios with unclear intentions or no prioritisation of cyclists.

The use of eHMI was particularly valued by respondents, aligning with previous studies suggesting it could enhance trust in HAVs, despite concerns about its readability at higher cycling speeds. Additionally, prioritising cyclists in scenarios was well-received, highlighting a preference for HAVs that demonstrate predictable behaviour. This predictability was favoured by respondents as essential for safe interactions in mixed traffic environments, contrasting with scenarios involving ambiguous or unpredictable HAV behaviour.

The driving dynamics of HAVs also influenced perceptions, with scenarios featuring clear deceleration or predictable behaviour garnering higher ratings for perceived social behaviour. Respondents expressed scepticism about fully replacing human drivers with HAVs, mentioning concerns about reliability, unpredictability based solely on sensors and difficulty in recognising HAVs on the road. Expectations included HAVs mimicking human driving behaviours and clearly indicating their intentions to improve safety and interaction with cyclists and other road users.

In essence, the survey highlighted the importance of clear communication, predictability and the role of technology like eHMI in shaping cyclists' attitudes towards HAVs in urban settings.

5.2. Limitations

The study identified several limitations that could impact the interpretation of its findings. Firstly, the small number of expert participants (only 4) suggests a need for a broader range of expert perspectives to strengthen the conceptual framework. Future surveys could enhance realism by using virtual reality or real-life experiments to better simulate cyclist-HAV interactions, addressing concerns about respondents not fully engaging with hypothetical scenarios in online questionnaires.

Additionally, there were concerns about response validity due to the potential for hurried or superficial responses and the influence of social desirability bias. The absence of hands-on experience with Highly Automated Vehicles (HAVs) among respondents also limits the empirical basis of their opinions, often derived from hypothetical scenarios rather than real-world encounters.

Moreover, the demographic composition of the sample, largely drawn from Delft University of Technology, skewed towards a younger, male and highly educated group. This limits the generalisability of findings beyond this specific demographic and geographic context, particularly concerning attitudes towards new technologies like HAVs.

Furthermore, issues with survey design, such as frequent use of "Other" responses in scenario-based questions, highlighted potential biases that could be addressed in future research methodologies.

To improve future studies, efforts should focus on diversifying participant demographics, exploring real-world environmental factors' impact on cyclist behaviours and refining survey methods to capture nuanced responses more accurately.

5.3. Recommendations

Taking into account cyclists' positive responses to eHMIs, future research should focus on optimising eHMI designs and communication methods to improve Trust, Perceived Safety and Perceived Social Behaviour among cyclists. Long-term studies are needed to monitor changes in cyclists' perceptions and behaviours as HAV technology evolves. Furthermore, interdisciplinary approaches will improve understanding and help develop better HAV systems. Additionally, research should explore the impact of policy frameworks and environmental factors (e.g., weather, lighting) on cyclist-HAV interactions to improve safety.

6. Conclusion

Analysis indicated that cyclists tend to feel uneasy in situations perceived as uncertain or unpredictable, particularly when dealing with the intentions of HAVs, as seen in scenarios involving unsignalised intersections. A widely accepted strategy to address these concerns, supported by survey respondents, involves the use of eHMIs by HAVs. Implementing eHMIs appears to positively impact cyclists' Trust, Perceived Safety and Perceived Social Behaviour regarding HAVs. Furthermore, individuals' comfort levels sharing roads with HAVs and their cycling frequency were also found to positively influence Trust, Perceived Safety and Perceived Social Behaviour. Moreover, the adherence of HAVs to rules significantly enhances Perceived Safety and Perceived Social Behaviour, surpassing the impact of various scenarios analysed. Interestingly, demographic factors did not exert a notable influence on participants' perceptions of their interactions with HAVs in this study, contrary to findings in other research.

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